An Early Warning System for

Risk Management

PhD Thesis

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degree of Doctor of Philosophy

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Declaration of Authorship

I, Amr Mohsen Jadi, declare that this thesis entitled An Early Warning System for Risk Management and the work presented in it are my own and original. It is submitted for the degree of Doctor of Philosophy at De Montfort University. The work was undertaken between October 2009 and October 2013.

AMR MOHSEN JADI

Dedication

To My Beloved Parents

The thesis is dedicated to my loving father, **Mr. MOHSEN ABBAS JADI**, who has been a great source of motivation, inspiration and endless support throughout my life and who sacrificed a lot for me to be what I am now. It is also dedicated to my loving mother soul, **Mrs. ZAINB TAWFEEQ SALAM** who gave her love and support, for everything she sacrificed in her life for me. Without her loving care, prayers and support, it would have been very difficult for me to achieve my life objectives.

To My Beloved Wife and Daughter

I would like to dedicate this thesis to my beloved wife **Mrs. TAGRHEED TALEEB and Liali Amr Jadi**.

I owe everything I have achieved or will achieve to them. I hope that by obtaining my PhD I can put smiles on their faces and happiness to the soul of my mother.

Abstract

Risk management in healthcare has solved a wide range of healthcare-related issues in Saudi Arabia. However, the limitation of risk management teams working under special conditions (needing to solve critical health-related issues) has highlighted the urgent need for an early risk warning system (ERWS) in healthcare. The influences of changing weather conditions demand that diabetic patients and doctors in Saudi Arabia have a continuous check on health conditions. The number of diabetic patients is increasing rapidly in Saudi Arabia. Hence, risk management teams in healthcare must be supported with a system that alerts to changes before the changes become a significant risk/problem. Our proposed approach does the following: 1) predicts changes in BP and blood sugar level within hospital environment at runtime. 2) Continually checks patient health status with respect to health condition at runtime. 3) Alerts to the changes as detected (e.g. risk or unknown parameter), and also provides feedback for patient and doctor.

We present a computational model that defines the interaction and communication of the system components and describes the prediction and checking process in our proposed approach. We designed the architecture for our proposed approach with respect to the computational model.

The thesis proposes an early risk warning system approach, which predicts and checks patient health conditions with respect to the ideal conditions according to medical standards. The health status of a patient will be communicated to doctors and patients on an emergency note if the predicted values are outside normal conditions. In this way, the risk can be mitigated before the occurrence of damage to patient health at runtime. To implement the proposed approach, neural networks is used for developing the prediction component using Java programming.

The results of this research successfully predicted the health condition of a patient by checking outputs against medical standards. The risks defined in this research include hyperglycaemia, hypoglycaemia, hypertension and hypotension. Appropriate results were obtained for almost every patient when checked with four input parameters for 200 patients. Consistent results were produced by the risk prediction component and the

alerts were generated after every five (5) seconds to communicate to the patients and doctors at runtime. Health status of all 200 patients can also be seen to check the changes in health conditions in the hospital environment. Finally, a case study with different scenarios based on changes in patient health status with respect to ideal conditions revealed evaluated the approach.

Acknowledgement

First and foremost, I humbly thank Allah who gave me health, thoughts and cooperative people to enable me achieving this goal.

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Publications

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Listings

Abbreviations

ADA	: American Diabetes Association
BMI	: Body Mass Index
BP	: Blood Pressure
CGM	: Continuous Glucose Monitors
DB	: Database
DM	: Diabetes Mellitus
ERWS	: Early Risk Warning System
EWS	: Early Warning System
HIV	: Human Immunodeficiency Virus
HM	: Healthcare Management
HMM	: Hidden Markov Model
IDDM	: Insulin Dependent Diabetes Mellitus
ISO	: International Organization for Standardisation
MODY	: Maturity Onset Diabetes of the Young
NN	: Neural Networks
NIDDM	: Non- Insulin Dependent Diabetes Mellitus
PID	: Patient Identification
QMS	: Quality Management Systems
RM	: Risk Management
RPC	: Risk Predication Component
SQL	: Structure Query Language

Chapter 1: Introduction

Objectives

- To motivate the need for an early warning system for risk management
- To highlight the original contribution and identify the research questions
- To present the aim and objectives
- To provide the original contributions and research methodology
- To provide the thesis structure

1.1. Background

Risk management in healthcare is playing a key role towards identifying the risks involved in various operational activities along with the problems related to patient health issues. The issues related to most of the physical environments were solved using risk management, but these methods have been problematic when addressing patient health conditions. Considering the issues related to the health of a patient, risk management teams are providing solutions for already identified and mitigated risk parameters [1]. For example, consider that the patient with diabetic mellitus will be treated if the health problem is already identified and mitigated [2]. However, any new change in health condition will not have a solution at that particular time. The patient will need to visit another hospital, or will need to wait a long time for treatment if risk mitigation is taking a long time. The risk management team using traditional methods could not predict the risks in advance nor could they provide solutions for the patient in time.

Such situations demand an early warning system even in the presence of a risk management team to provide better treatment for patients. Most of the diabetic patients in Saudi Arabia are visiting hospitals only when their risk levels are reaching a maximum extent. Some of the patients do not even know the risk they are facing due to lack of early detection. Hospitals do not have solutions until they understand and mitigate the new risk parameter, and using traditional methods, the process of risk mitigation only takes place after damage to patient health[3] [4] [5]. Healthcare practice demands a careful and attentive system that provides an early warning of risk levels at runtime.

This thesis considers an ERWS approach that is based on patients with diabetes. Patients' blood sugar and BP levels are monitored, predicted in the hospital environment with a well-established early risk warning system approach. This approach can overcome some of the problems experienced by healthcare centres in Saudi Arabia. The following sections outline the problem statement and research aims.

1.2. Problem Statement

The number of patients with diabetes is increasing in primary healthcare centres in Saudi Arabia due to the lack of an early detection program. Patients with these problems experience various risk factors such as atherosclerotic cardiovascular, peripheral vascular and cerebrovascular diseases [6]. The results of a study conducted by a military hospital in Saudi Arabia revealed that more female than male patients experience diabetes. These patients face problems due to a lack of awareness and knowledge of precautionary steps to be followed during high-risk times. Patients have reached an abnormal condition by the time treatment is given. The only method/approach followed by Saudi Arabian patient's demands that the patient visit the hospital to determine health status under the supervision of a physician [7]. At times even the physician will not be aware of the magnitude of the patient's illness, leaving him/her unable to promote suitable treatment/better care. Apart from that, even in hospitals, a doctor needs to monitor patient conditions continuously during high-risk times [8]. This entire process needs an approach that can alert patients and doctors when the risk levels of patients are going beyond the control levels. Hence, the current healthcare system needs a method wherein patients, doctors and the hospital management team receive alerts when risk factors are reaching uncontrollable levels.

The research aim and objectives are drawn based on the above discussion to propose a systematic approach for an early risk warning system.

1.3. Research Aims and Objectives

Aim: To propose an early risk warning system approach for risk management of healthcare in Saudi Arabia.

Objectives:

1. To address the major problems of healthcare centres in Saudi Arabia using risk management.
2. To address different risk types in diabetics according to medical standards.
3. To collect BP and blood sugar levels of 200 patients from a hospital in Saudi Arabia for testing the proposed approach.
4. To develop a computational model that is suitable for the proposed approach.
5. To design the architecture of the proposed approach in a way that fulfils the needs of risk prediction and runtime monitoring.
6. To implement a prototype of the ERWS approach that is suitable for a hospital environment.
7. To evaluate the proposed approach with respect to medical standards using a suitable case study in healthcare.

1.4. Research Question

The research proceeds with the following research questions suitable for the proposed research:

- How to establish monitoring of healthcare at runtime to continuously check patient health conditions?
- How to predict BP and blood sugar levels at runtime in a hospital environment?
- How to communicate with the patient and hospital management team when a risk/unknown parameter is detected after the checker process?
- How to establish interactions between components of the proposed architecture?

1.5. Original Contributions

This research develops an early risk warning system approach to ensure that the patient is getting better treatment. The changes in health conditions are monitored and these changes (blood sugar and BP levels) are mitigated continuously by alerting patients and doctors. This process not only allows doctors to provide better treatment but also helps patients to understand the necessary precautionary steps to be taken for immediate effect. Apart from this, the role of risk management teams in healthcare will be improved by involving them in mitigating unknown parameters at runtime. The key contribution of this research is towards collecting the real information of patient’s from the hospital environment to test the proposed approach.

The technical contributions of this research are:

C.1. Chapter 3 develops the computational model for the ERWS approach based on real patient information in the hospital environment. The computational model will describe the role of different units of computation and define the risk notion.

C.2. Chapter 4 proposes architecture for an early risk warning system approach suitable for healthcare at runtime. It has four components including Hospital Environment, Risk Prediction, Runtime Monitoring and Hospital Management Team.

C.3. Chapter 5 develops the prediction and checking functionalities for the proposed approach that meet the specifications of medical standards. To develop this approach, concepts of neural networks are used by implementing in Java.

C.4. Chapter 6 develops a prototype of the ERWS approach suitable for the hospital environment using neural networks and Java. The SQL trigger techniques are used to generate alerts with feedback for patients and hospital management teams.

C.5. Chapter 7 provides the case study with different scenarios used to evaluate the proposed approach. The evaluation will show the results of the prediction and verification of the unknown parameters form the blood sugar and BP levels of patients with respect to medical standards at runtime.

1.6. Research Methodology

Selecting the suitable method for performing research is an important area that needs careful attention. The reason it is such an important area is due to the nature of producing quality output for the researcher [9]. According to domains, research methods are changing, and while not all the possible methods can be explained in detail, a brief summary of each method is discussed below [10]:

- **Fundamental Research:** Used to improve the knowledge of an area without applying any specific purpose. It mostly creates an overview of topics and highlights from different sources of information.
- **Conceptual Research:** Used for developing or reinterpreting a concept. This method is generally used by academicians to create summaries of theories with the aim of learning or advancing to a new concept.
- **Exploratory research:** Evaluates new problems within a defined field. It explores the existing theories in detail to provide mathematic or theoretical proof [24].
- **Empirical Research:** Applied on broad empirical studies to understand the advantages and liability of the concepts and to realise the solutions for large-scale information.
- **Action Research:** Provides solutions for current problems generally related to society, industries, business units etc.
- **Experimental Research:** Based on the demands of a particular hypothesis.
- **Non-Experimental Research*:*** Does not need a hypothesis to conduct research.
- **Qualitative Research:** Based on the researcher’s involvement directly in finding solutions. Conclusions of this type of research are drawn based on the contributions and observations of the researcher [12].

- **Quantitative Research:** Engages the researcher in conversations and observations in order to understand the opinions of people with a different mindset [12]. This research might not always need the direct participation of the researcher.

Apart from these, data collection is another key aspect of a research process, of which there are two types: 1) Primary Data and 2) Secondary Data [13]. Secondary data is collected from the available resources such as books, journals, publications, internet articles etc. Primary data are collected by the researcher with the specific purpose and interests related to a particular research aim and objectives.

In this research, the approach used is ***constructive research*** for developing a solution to existing problems. Though there are solutions, those available may not be suitable for providing solutions for the new problems that come with time and changes in environment. This type of research refers to a method for developing a new technique and model/framework, along with new algorithms [14]. Hence, the research approach selected here is the constructive approach, which is suitable for the demands of the research undertaken. This method is also considered a part of computer science for importing new tasks to develop, implement and evaluate the proposed approach [15].

The proposed approach was developed according to the following steps in this research project:

- **Step 1 Selecting relevant problem potential outcome in Chapter 1:** This step provides an overview for the problem of healthcare with the aim of predicting the risks and unknown parameters in the hospital environment for diabetic patients. Suitable methodology was also discussed to fulfil the needs of this thesis.

- **Step 2 Conduct Literature Review in Chapter 2:** This section provides the explanation for the theories selected to implement the proposed approach. A detailed investigation takes place to identify the different types of risk prediction and monitoring methods. A critical review of the existing concepts of risk management illustrates limitations and challenges.
- **Step 3 Constructing an approach for providing solutions in Chapters 3 to 5:** This step develops the computational model that explains the complete behaviour of the system. It also explains the architecture and its components. It explores how the risk prediction takes place at runtime with appropriate steps. It also explores the implementation of runtime monitoring used in the proposed approach.
- **Step 4 Demonstrating the working approach in Chapters 6 and 7:** A prototype was developed based on the approach to solve the problem defined in the research questions, and the implementation was performed using Java. The evaluations justify the achievements of the developed architecture.
- **Step 5 Summarizing the research contribution:** The proposed approach satisfies the needs of healthcare providers to predict the risk at runtime in a hospital environment. It allows the risk management team to mitigate the health problems of patients at a much faster rate, as the

predication process is finished in far less time than the traditional method.

1.7. Thesis Outline

According to the objectives of the work, this section provides an overview of the remaining chapters of this thesis along with a summary of their contents:

Chapter 2: Background and Related Research

This chapter gives an overview of risk management in healthcare systems, healthcare system functions and methods in Saudi Arabian hospitals, runtime monitoring and risk prediction using neural networks. The importance and role of risk management is explained in this chapter along with its limitations to provide solutions for the unknown parameters at runtime. The basic components of runtime are explained, along with their role in present research. The applications of neural networks are discussed, and the roles of neural networks are discussed in various other healthcare applications.

Chapter 3: Computational Model

In this chapter, the computational model introduces the early risk warning system with risk notion for the proposed architecture by informal description. This first part explains the computation and shows how the components communicate and collaborate with each other [16]. The process of predicting, checking and communicating the feedback is given in the computation of system components. The second part of this chapter gives an overview of neural networks and this method's principles in detail.

Chapter 4: Architecture

This chapter gives an overview of the proposed architecture. It is classified into four sections: hospital environment, risk prediction component, runtime monitoring and hospital management team. The chapter presents the aim of early risk warning in system architecture. It describes the concepts of each component and shows the interaction between each component. This chapter also describes different components and their interactions, and the communication [79] of feedback. This chapter also explains the methods of risk prediction in detail, and explains the implementation of runtime monitoring and its components. The functionalities of the checker and its roles are explained in detail. Additionally, this chapter explains the hospital environment and hospital management team and their role in the proposed concept.

Chapter 5: Risk Prediction and Runtime Monitoring

This chapter aims to define the role of the risk prediction component towards predicting risk at runtime. The first part of this chapter explains the prediction component using neural networks and describes how it was implemented in Java. The second part explains the runtime monitoring and how the checker checks the predicted values against the ideal values that are stored in the database.

Chapter 6: System Prototype

This chapter represents the prototype implantation of the proposed approach (ERWS). It provides an overview and description of the technology used to develop the approach [17]. The components and attributes of the prototype are explained in detail. This chapter maps the components and describes the system architecture's components. Finally, a class diagram is shown to draw the relationships between different classes.

Chapter 7: Evaluation

Evaluation of various components is provided in this thesis using a case study. This case study explains the use of different scenarios to analyse the outcomes of the risk prediction unit, identifying risk levels as per the standards of medical associations. Based on the predictions, the alerts are shown in the doctor's screen, and the complete patient information is shown in the database.

Chapter 8: Conclusion and Future Work

This chapter summarises the research and proposes future work.

Chapter 2: Background and Related Research

Objectives

- To give the background of risk management in healthcare
- To give the limitations of risk management in healthcare
- To give an overview of runtime monitoring
- To give an overview of neural networks for an early warning system

2.1. Introduction

In this chapter, the literature review and background of basic concepts were critically analysed for their role in the present research. The principles of risk management and its useful advantages for the healthcare industry are explained in section 2.2. Major advantages and the role of risk management in scoping the problem are explained in section 2.3. The importance of runtime monitoring and the different components involved with the runtime monitor are explained in section 2.4, in order to draw attention to its need in monitoring patient health conditions in the hospital environment. Usage of neural networks as a risk prediction component and early warning system are explained in section 2.5, along with neural networks properties as suited to our proposed research.

2.2. Risk Management

Risk management (RM) in traditional healthcare aims to protect against the risks associated with all kinds of accidental losses, etc. The ultimate goal of RM in the healthcare industry is to have sufficient coverage of all kinds of potential sources of risk [18]. For an effective healthcare system, the risk management program must concern a variety of issues and situations responsible for all kinds of casualties in the organization. In early days, risk management issues were related with medical professional liability claims and insurance premiums [19]. However, in the present market focus is mostly on safety issues related to patient care issues. Patient-related risk management considers treatments performed incorrectly, issues related to confidentiality, protection for patients from abusive language by other patients, securing patient medical treatment information and involving patients in support for experimental drugs and medical procedures. Apart from these risks, there are many other issues RM covers in the healthcare system related to medical staff-related issues, employee-related risks, property-related risks, financial risks and many other risks related with the hospital environment [18]. Managing these risks aims mainly to prevent or reduce loss in the healthcare system by segregation and separation according to the type of risk. However, there are few key elements RM considers in healthcare, including authority, visibility, communication and accountability. The success of healthcare depends on these variables by attending to structural factors within the hospital to ensure a solid foundation [20]. In this research, focus will be on the risks related to diabetic patients and the role of the risk management team in making appropriate decisions while mitigating the unknown parameters in the newly proposed approach.

2.2.1. Process of Risk Management

Risk management begins with the identification of possible risks in an organization. The identified risks are prioritised and analysed carefully under the guidance of experienced persons at the level of senior doctors and above. A plan is created to identify actions that will resolve the risk or reduce damage so that the identified risk will not become a problem [21] [22]. A brief example of the risk management process is shown in Figure 1. Containment action within the project plan was implemented according to the actions considered in planning. In the meantime, the process was tracked and risk parameters listed as a part of risk reduction actions. Tracking also helped to add new risks or to find those risks adjacent to the known risks. After selecting the best RM technique or treatment, the method for a specific situation is a two-part activity [18]. The effect is forecast with the available risk management technique, but risk management also worked to obtain new information and, according to the new status, the plans were updated.

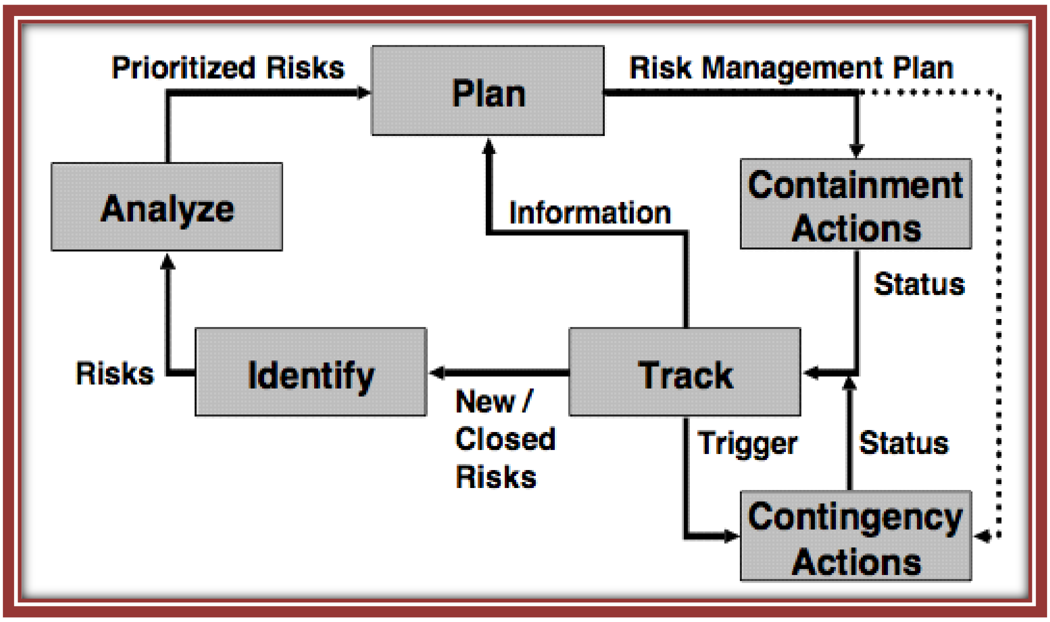


Figure 1: Process of Risk Management

In the healthcare industry, risk management professional must investigate vast data from various sources and identify the key events and functionalities in hospitals that may create problems or risks [8]. Risk managers in healthcare have always worked as negotiators in different situations and acted as an intermediary between patients and management by identifying the key risks, then analysing and resolving them in order to run smooth operations.

2.2.2. Role of Risk Management in Healthcare

Risk management applications have been used in healthcare systems in different ways to avoid failures due to different factors like constraints, unresolved issues with patients and not meeting patient demands [23]. Hence, risk management plays a key role in most healthcare applications and project development activities as it deals with expected functionalities, changing opinions, actions and various other factors that tend to change abruptly [24]. The characteristics of risks in any healthcare setting involve two main parameters: ***uncertainty*** and ***loss*** [91]. In the first case, the likelihood of the risk to happen is not 100% and it could happen any time. In the second case, the risk has become a reality and unnecessary losses are bound to happen [24] [25]. Executing risk management in healthcare systems demands serious attention while working with patients and their health problems. Healthcare systems involve a wide range of challenges and keep doctors on their toes when facing new health problems with a patient due to sudden changes in environment/accidents. However, Misra *et al.* also highlight the importance of ***severity*** of the loss and ***duration*** of the risks as two other key issues widely considered by RM [25]. Healthcare systems organize the risk levels of patient health status with standard approaches by defining the risk index of various parameters after a careful analysis and assessment.

- **Risk index**

The doctors along with the RM team test the probability of possible situations/impacts where there is probability that a risk event may occur. The multiplication of risk impact and probability of occurrence defines the value of the risk index [24]. This index could be very high, medium or low based on impact and occurrence.

- **Risk analysis**

Risk analysis of a newly identified parameter will define the high-risk elements and methods of risk mitigation strategies, which are already in use. Analysis of patient health conditions is an important phase of the healthcare unit for evaluating the level of risks in the defined parameter. A successful analysis/mitigation process includes key elements of the problem by formulating various scenarios using data collection methods [24] [90].

- **Risk assessment**

Risk assessment requires an appropriate explanation about the failures and features of a health problem [24]. To assess the risk of a patient, doctors need to maintain a good record of previous studies and evaluations made earlier. A regular process of risk identification, mitigation, monitoring and producing a quality treatment for the patient is the responsibility of a healthcare system. If this analysis produces a new risk parameter after the mitigation process, doctors and RM teams are more able to control serious damages. The RM team along with doctors can eliminate or at least control potential side effects from newly identified risks. Boehm and Marco explain that risk exposure is key for risk management. Risk exposure is a product of the probability of potential loss by the size of the loss [1].

- **Risk management team**

A systematic risk management method is implemented in a healthcare system to manage the project risks. The management team identifies the risks in order to evaluate and prioritize them for mitigation and develop solutions after the mitigation process. By regularly monitoring these plans, the effectiveness of the proposed solutions to reduce the risks will be defined [23]. This approach helps healthcare systems to reduce risks by taking additional steps to correct necessary actions needed at different levels of patient interaction with doctors. The process of a healthcare system will follow the life cycle [23] as explained in Figure 2. The parameters of the life cycle in a healthcare system throughout the year can be explained as follows:

- Identifying the risk
- Analysing the risk
- Planning
- Tracking
- Controlling
- Communicating

Figure 2: Risk Management process for managing risks

***Identifying the risk*:** In this identification process, the uncertainties and various health-related issues are transformed into tangible parameters. Tangible parameters are clearly described and experts and doctors carry out an assessment process in the hospital [23]. There are two methods for identifying a new risk: i) by considering and recording various conditions that are causing concern for a patient; and ii) by examining the context of the risk, including the recording process of additional information regarding circumstances, events and interrelationships within the duration of the problem's occurrence [23].

Analysing the risk**:** Risks are examined at every stage in detail to analyse the needful solutions for a patient health problem. Senior doctors and experts with relevant backgrounds will discuss and collect the information related to new problems and issues and evaluate the risk levels.

Planning**:** According to the level of risk, the planning process will define the stages of treatment. The senior doctors will generally decide the suitable steps of planning procedures with regard to the patient problem(s).

Tracking**:** In this process data are collected from various doctors and technicians to start the mitigation process [23]. The parameters gathered during the tracking period are used during the planning process, and the decision-makers (RM team) use the same information for defining new risk levels.

Control**:** In this process, decision-makers analyse the data available in the tracking reports to make decisions. The person responsible for the patient will make decisions with possible solutions for the newly identified risk [23].

Communication**:** This is one of the most important parameters of the entire risk management system, as most times people find it difficult to address the identified risks [23]. Lack of proper communication skills raises difficulties for risk management teams in software companies, and they find it very difficult to assess risks due to these problems. Failure in communication usually leads to total risk management failure in hospitals [19].

2.3. Scope of the Problem in Healthcare Systems

The health services across many European countries are similar. Though changes in medical treatments are similar and operating on the same principles, sometimes patient approaches and treatments will change due to factors such as changes in climate conditions in different countries. Present research deals with diabetic patients in the hospital environment. Almost 23.7% of adults in Saudi Arabia are diabetic, and the government is running targeted initiatives to prevent high-risk, badly-affected groups [7].

The diagnosis of Diabetes mellitus (DM) in this research is based on the American Diabetes Association (ADA) expert committee recommendations. These standards are followed in Saudi Arabia, and they propose FPG≥7.0 mmol/l for DM and IFG 6.1 – 7.0 mmol/l for impaired fasting glucose. Non-diabetic patients will have FPG 6.1 mmol/l [6]. Patient’s health conditions in different conditions within the hospital environment were tested to check the changes in blood sugar and BP levels of 200 patients from a Saudi-based hospital. This research provides an early risk warning system to predict risks in runtime. As discussed in the above sections, the risk management techniques implemented in healthcare systems mitigate risks only after the problem is identified. The time taken to predict risk is comparatively very high, and the probability of maximum damage is high when using traditional healthcare system methods. The risk parameters defined by medical standards have been considered, and the proposed approach will test the current condition of the patient on a regular basis. The goal of this research is to propose a method where the patient and healthcare system will be alerted when a patient health status becomes high-risk or when a new parameter is identified.

2.3.1. Risk Management and Its Role in Healthcare Application

Risk management plays a key role as a safeguard in managing and operating the healthcare industry's operations smoothly. Most companies follow various standards of risk management for the healthcare industry to satisfy various regulatory requirements at the international level in order to sustain in the markets long-term. International standards are especially designed for risk management in maintaining medical devices based on ISO 14971 standards [26]. These standards assist the healthcare industry and manufacturers in establishing, documenting and maintaining the risk management process in order to:

1. Identify the critical hazardous conditions and various hazards in the regular process,
2. Estimate and evaluate risks based on the priority at different levels,
3. Properly plan how to control the risk, and
4. Monitor on a regular basis with effective controls to make an appropriate product life cycle.

Apart from these, the risk management team also tries to identify whether a healthcare industry has a policy for risk identification. The team checks the links from all the quality management systems (QMS) for the risk management process.

However, as per the discussions of UL companies [26], the risk management team must also allow the management to effectively conduct internal audits at different levels.

2.3.2. Role of Risk Management after Deployment

The roles of risk management are to enable a safer implementation of the process designed by experts and to avoid unnecessary activities to operate in a timely fashion and within the planned programs. Risk management allows the system to apply intensive testing at each stage to avoid most of the risks that would occur at runtime [26]. The risk management process has created a reasonable standard in hospitals to initiate after deployment, reduced modern risks, and helped the management to reduce financial risks or risks due to human error [124]. These techniques have identified good monitoring systems to resolve new risks found in real-time operations. The designed risk management system for any organization not only mitigates current risks but also tries to extend its applications to make the process more effective at predicting new risk in real-time applications [27] [125]. The highest risk occurred with risk management systems after deployment due to abrupt malfunction, or unexpected or unnecessary stopping by any of the key elements.

The main purpose of a deployment phase is to place the identified solutions and plans into the real-time environment. This phase is necessary to support the technology and components, and to stabilize and support the operations of the environment [28]. After deployment, a tracking team conducts the review process of the events and tries to identify the newly occurring events or the events expected during the planning process. Surveys are conducted to collect feedback from the performances, and the stabilizing process takes place during the same process.

2.3.3. Problems in Risk Management after Deployment

After deploying risk management in healthcare, most hospitals identified few risks that evolved at runtime. The major problem experienced by the healthcare industry after deployment was of no use to predict risk in early stages. Risk management could not solve the problems related to changes in environment and the changing demands of hospital needs [29]. During serious disasters, risk management could not provide suitable solutions for patients in the period after deployment. Apart from this, risk management could not identify the unknown parameters in runtime and had no solution for patients with new types of health problems [126]. The traditional method could not mitigate any problem at runtime and it held the capacity to understand the new problems with new parameters only when the problem/damage had already affected the patients [127]. Prediction and mitigation of risk at runtime was not possible by risk management after deployment [113] [114]. Hence, it was found that an early warning system was needed for healthcare as an essential tool to solve problems in their early stages.

2.3.4. Limitations of Early Detection Program in Healthcare of Saudi Arabia

Risk management plays a key role in addressing major problems in healthcare services. The problem of an increase in the number of diabetic patients in Saudi Arabia has been seen in the last few decades. Due to the nature of the current hospital environment in Saudi hospitals, patient problems are not addressed immediately with proper solutions. Even risk management teams have been unable to find a solution for the evolving risks. They have not been able to provide an early detection method for predicting the risk parameters that evolve over time [30] [106]. Due to the lack of an early detection program in Saudi Arabia, most patients in various urban regions do not know their current health conditions. In the meantime, according to Al-Nozha *et al.*, more than 27.9% of Saudi adults are unaware of having diabetes mellitus (DM) [116] [117]. Most patients are suffering from various health problems but are unable to self-assess, hence the tendency toward serious health problems is greater. The study conducted by Osaimi [7] identified that the number of female diabetic patients is large; 50% greater than the number of male patients. The research revealed that patients aged 35 and above were tested and DM found in 8.5% of males and 19.48% of females in a Saudi military hospital [119] [120]. The detection of diabetes in Saudi Arabian hospitals revealed that there is no relevance between diabetes and the physical activities of patients to identify the actual cause for the risks [105] [106].

The proposed approach aims to provide an early risk warning system for diabetic patients where the health status of the patient is monitored at runtime and the prediction process takes place continuously [107]. With this approach, the health condition of a patient will be observed and feedback can be given to the patients by predicting risk levels based on patient health status. Due to the lack of this kind of early detection program, many patients suffer serious problems in Saudi Arabia [30] [104] [118] [121]. The risk management team also cannot effectively help patients and update the hospital management team until the patient's health status is critical.

2.4. Runtime Monitoring

Runtime monitoring is used to check system properties to test whether specifications are satisfied. Runtime monitoring verifies the execution paths and identifies the faults at runtime by checking all possibilities [31]. Runtime monitoring is dynamic analysis in which the process will be checked as the system is executing. This research uses runtime monitoring for checking the health condition of the patient at runtime.

2.4.1. Dynamic Analysis

Dynamic analysis requires two basic components: monitoring and verification mechanisms. The first component will identify the events as they are happening. These events will be communicated with the second component for verification. The second component verifies the order of events and checks with the system specifications [103]. After identifying any kind of difference from the defined specifications, the verification mechanism raises the alarm and possibly gives feedback to the actual system [32] [108]. The phases of dynamic analysis [32] are explained in Figure 3.

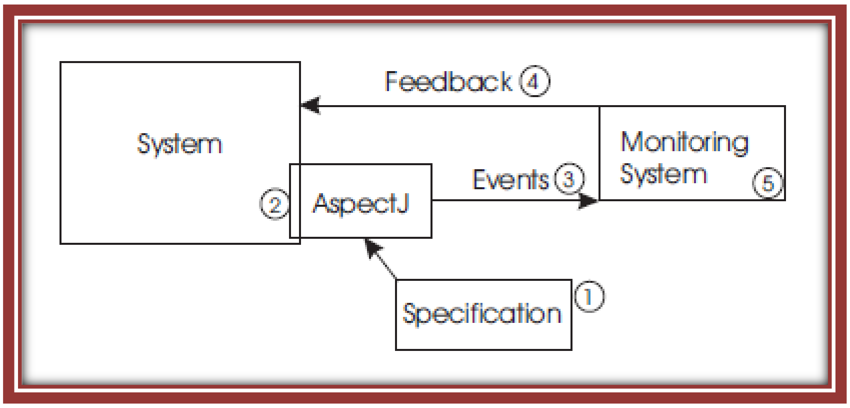


Figure 3: Dynamic Analysis Phases

A kind of formal notation is given in the system specifications. The domain problem will provide the notation choice. These specifications will be instrumented in a system code. However, in some systems the code is instrumented in target code. System monitoring can be done using offline or online methods. This means the monitoring mechanism will be running synchronously and/or the system execution will be saved later. In the next phase, expectations will be raised and errors will be detected. When the system detects a problem/error, it conducts an automatic mechanism to correct the issue. The mitigation phase will be used to minimise the problem impact and reduce the problems [32].

2.4.2. Static Analysis

In a static analysis, code will be used to verify the program in all paths ahead of the actual execution of programs. The mitigation and checking process in this method will be done before the actual process takes place [109]. However, in dynamic analysis, the mitigation process takes place while the system is running. The objectives in this method are desirable and all possible paths are verifiable. The problem in a static system arises when the magnitude of the system variable is increasing and it becomes largely unattainable [32].

Simply put, the dynamic systems checker will check the system properties with the execution path continuously. It is useful for identifying errors and mitigating them immediately. This method ensures that the system is not violating the system properties during the execution time.

2.4.3. Checker

The checker is an important component in the proposed approach and is used to check input values against the ideal conditions of glucose and BP levels. The checker collects the ideal conditions from a database (provided according to the medical standards) and checks the output of the RPC. The process of checking is continuous in the proposed runtime method. The corresponding outputs of this section will be provided to the patient and database for further mitigation processes in case of identifying the error values.

2.4.4. Mitigation

In the healthcare industry, the mitigation of risks will be based on the type of health problems identified by doctors in a periodic duration by making notes from careful observations. The level of risk is identified by combining the possibilities of severity of violations or attacks on a particular parameter when compared with standard medical reports [33]. The mitigation process in a healthcare system depends on the internal and external technical aspects along with other training aspects within the hospital. The mitigation plans will be developed at the final stage of a risk assessment and review.

2.5. Early Warning System for Predicting Risk

2.5.1. Properties of Neural Networks

There are many neural networks-based systems considered to be more effective due to their non-linear relation among the variables. These systems have mainly been learning systems that model the relations between various sets of inputs and outputs due to the nature of non-linear relations. These systems are considered black boxes as the extraction of symbolic information from the internal configuration is difficult. These systems are mechanical learning systems dependant on a simplified model of biological neurons [34] [111]. Biological neural networks change their parameters on their own to perform some cognitive and computational tasks. The major efficient and effective tasks performed by neural networks are classification, recognition of patterns, prediction of disease symptoms and identification of causes [35]. These neural networks models have also been a part of statistics-based scores [36]. However, two main issues exist with the application of neural networks typology: structure and learning algorithm [34].

2.5.2. Risk Prediction using Neural Networks

Risk prediction using neural networks has shown an accuracy of 82.2% in cardiac surgeries of healthcare applications [37]. The success rate of NN is very good as compared to any other method of risk prediction components. Most applications using neural networks produced an accuracy of above 65%. Considering all summaries made by Lisboa [37] ensures that use of NN is not a bad risk-prediction component, especially in the healthcare industry. Also, as technology has improved neural networks performance, accuracy in predicting risk increased largely, even to 98% in some health issues [37] [112] [122] [123]. The major advantage of this method is its ability to operate as a human brain while making decisions [101] [128]. NN is also applied for the risk prediction process like banking, security and other fields [39]. NN has robustness in giving accurate results, performing more accurately then other classical analytical methods in predicting and identifying disease.

2.5.3. Early Warning System Using Neural Networks

Neural networks methods have been used in most biomedical applications for the last 37 years. NN is a good drug-monitoring tool in both theoretical and practical applications [102]. In 1991, the concepts of NN were used for a drug interaction warning system in a computerized real-time medical recording system [38] [129]. In recent times, the uses of neural networks have even been applied to assess HIV immunopathology. The reasons for using neural networks are due to high variability, non-stationary and non-uniform sampling. High variability depends on the time of patient follow-up in the critical period. This is more convenient when monitoring patients closely within the reach of the hospital environment [130] [131]. Most of the early warning systems using neural networks turn out to be highly accurate in terms of monitoring and predicting risks, and in the medical industry they are proved to be effective in giving good results.

2.5.4. Justification for Neural Networks over Other Approaches

The advantages of neural networks are comparatively dominant over other techniques to use in the proposed architecture. Fuzzy logic is based on the approximate values, inference or ambiguity data, which were opposed for relying on crisp data [40]. The probability values were only between 0 and 1. The output values assessed by fuzzy logic could produce ambiguity among the output response in a runtime monitoring system where the parameters are observed continuously. However, in neural networks, values are based on the average response of the values based in the hidden layers. Even an error for a simple calculation, like 2+2 = 3.8, is acceptable to some level in risk prediction. However, in fuzzy logic, the value could be either 4 or 0. This kind of response using fuzzy logic makes a big difference in implementing this in a runtime monitoring system.

As discussed above neural networks are superior to fuzzy logic stability in terms of giving approximately correct output. However, fuzzy logic is much better suited to concepts that need subjective contexts and to differentiating potential conflicts from various contexts [115]. Apart from fuzzy logic, there are few other approaches that can be applied at runtime monitoring. They are probabilistic logic, Bayesian [41] networks and hidden Markov models [42].

Probabilistic logic uses logical assertions that are linked to different probability events. This logic is mostly based on proposition logic, where the comparison of different statements is considered to select an event [42]. This rule is generally used to improve the quality of a concept but could not be used in the present technique due to the involvement of a wide range of numeric numbers that are sensed by the runtime monitoring component [92]. Using probabilistic logic in the current proposed technique introduces possibilities of slow performance.

Bayesian networks are basically directed through acyclic graphs in which the nodes will be random variables representing different relationships. Properties of these networks include two joint distributions of set of variables as a product of local distribution of current nodes and related parents [42]. These tools are very powerful for predictive modelling and analytics [43]. However, these models are very much limited to identifying the risk related with various software parameters, bioinformatics and till marketing sciences [93]. They were not capable of identifying the risk related with physical equipment at runtime for the healthcare industry.

The hidden Markov model (HMM) represents stochastic sequences as Markov chains [42]. In this model, the states will not be observed directly but are linked with evidence, also known as emissions, in which probability of occurrence depends on different hidden states. It is generally used for predicting locations and is not suitable for the present technique as it once again depends too much on evidences and probability [94]. The present technique demands a process where the average output values meet the requirements of the nearest value of a risk to be predicted. In such situations, depending on the probability of an event to occur and making decisions by comparison are not suited for this technique. In brief, a wide range of the advantages of neural networks [44] is shown in Figure 4.

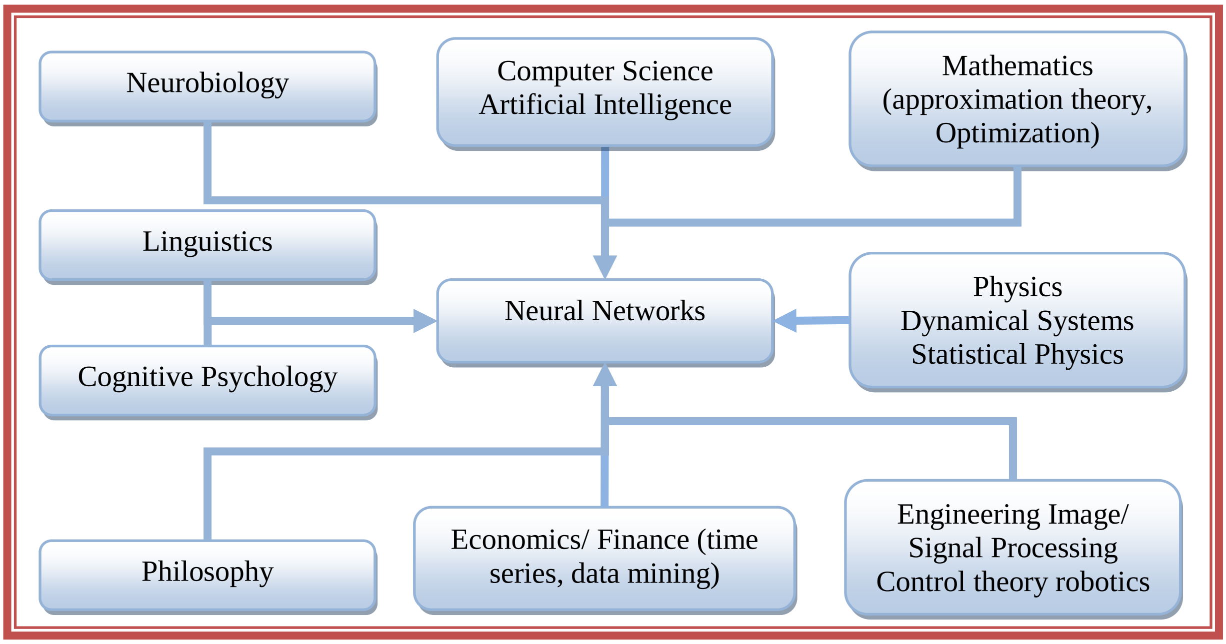


Figure 4: Various advantages of neural networks

2.6. Summary

The overview of the learning outcomes was discussed in the beginning of this chapter. A review of risk management was given and its applications in healthcare with limitations were explained. This chapter provided detailed study of three concepts: risk management in healthcare, runtime monitoring and risk prediction using neural networks. Risk management's role in healthcare has been a major contribution in solving most real-life problems. However, the inability to solve the health problems of a patient at runtime makes its impact very limited. A critical review of the involvement of risk management in healthcare revealed that it suffers from a lack of communication between hospitals and patients to identify/understand changes in health conditions. The proposed approach was the outcome of this limitation of risk management to predict and solve the problem, or at least to mitigate it in time. The need for an early warning system for healthcare was identified as a necessity, especially in the case of diabetic patients. For this purpose, various other risk prediction techniques were also considered, but neural networks had a good success rate in terms of predicting errors as discussed in section 2.5.3, and it is also capable of working with complex and large numbers. In the following chapter, the computational model is explained along with more detail about neural networks in the second part.

Chapter 3: Computational Model

Objectives

- To describe the computational model of the early risk warning system (**ERWS**)
- To provide an analysis of patient health status
- To give an overview of neural networks using Java

3.1. Introduction

This chapter summarises the computational model used to develop the proposed approach to predict the unknown parameters in runtime. The computational model and risk notion with respect to the proposed architecture are drawn in section 3.2, with suitable explanation. All the components of the computational model are discussed with appropriate justification for their role in section 3.3. The interaction between all components and communication methods is explained in detail with its importance for the proposed approach in section 3.4. The role of neural networks in designing the risk prediction component with suitable analysis is derived in section 3.5. The analysis of the back propagation algorithm is explained in section 3.6.

3.2. Computational Model

In this section much information is discussed about how the risks related to the proposed architecture would influence the patient's health condition. The health problems of ordinary diabetic patients related to blood sugar and BP levels have been highlighted and carefully analysed here. Hence, the risks related with the proposed architecture fall under the monitoring of this unit, and probable solutions are proposed to design a suitable architecture for the nearest results [45] [46]. This section introduces an informal computational model for an early risk warning system (ERWS) approach to predict changes in patient health conditions (i.e. BP and blood sugar levels) at runtime. Our model defines the communication and interaction between units of computations. In the hospital environment, the risks are mitigated only once: after the problem has already occurred. However, the proposed approach is a dynamic approach that can predict the risk in advance and allow risk mitigation by runtime.

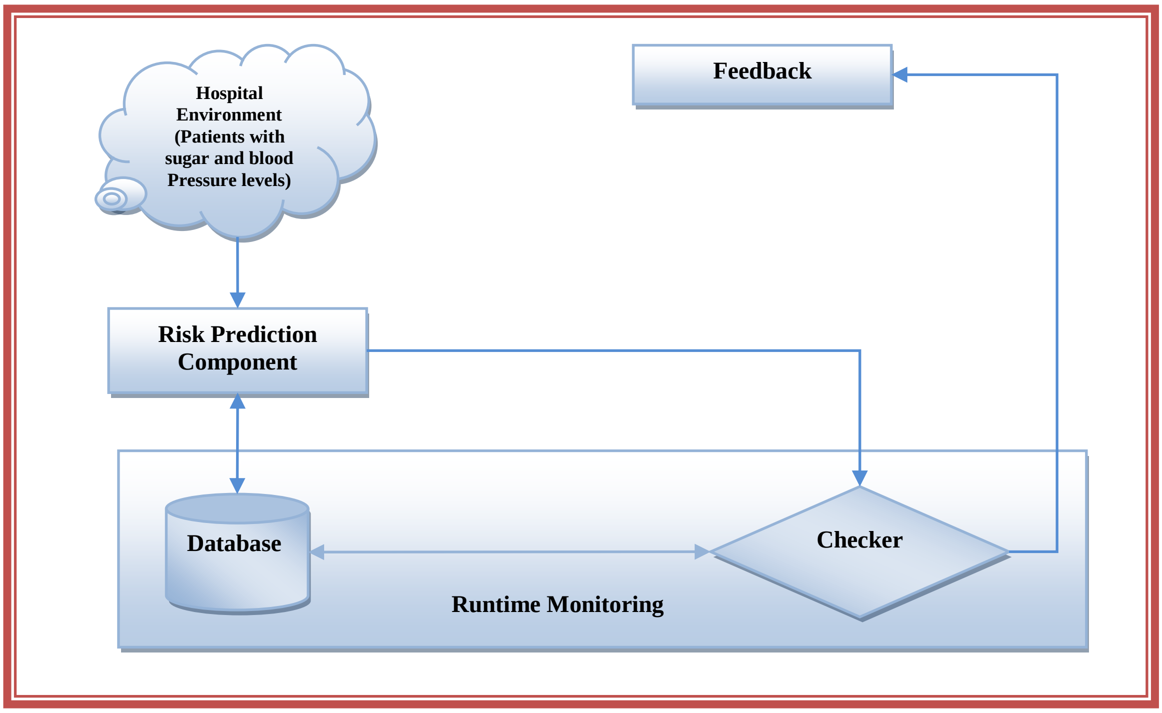


Figure 5: Computational Model

3.2.1. Risk Notion in the Proposed Architecture

In the proposed approach, risks were expected to occur with respect to patient health conditions. The risks were identified and defined according to medical science reports and standards. In this research, the blood sugar and blood pressure levels of a patient are examined at runtime. Risk levels are predicted and mitigated to alert the patient and healthcare system. In the case of unknown parameters observed at runtime, doctors are alerted for immediate action in the proposed research.

The entire research project intends to monitor patient condition at runtime, and risk levels are monitored at runtime to predict the health condition of a patient.

Identifying unknown parameters only will not be able to fulfil the objectives of this research; mitigating and identifying possible solutions are also within the objectives of this research.

In the proposed architecture, the objectives focus on various risk parameters involved with diabetic patients, and with blood pressure levels within the hospital environment. These risks include changes in the blood pressure and blood sugar levels of a patient. The risks related with blood sugar levels are defined as hypoglycaemia and hyperglycaemia, with various blood sugar levels in the human body in these two conditions. The first condition is connected to blood sugar levels before meals and second condition with blood sugar levels after meals.

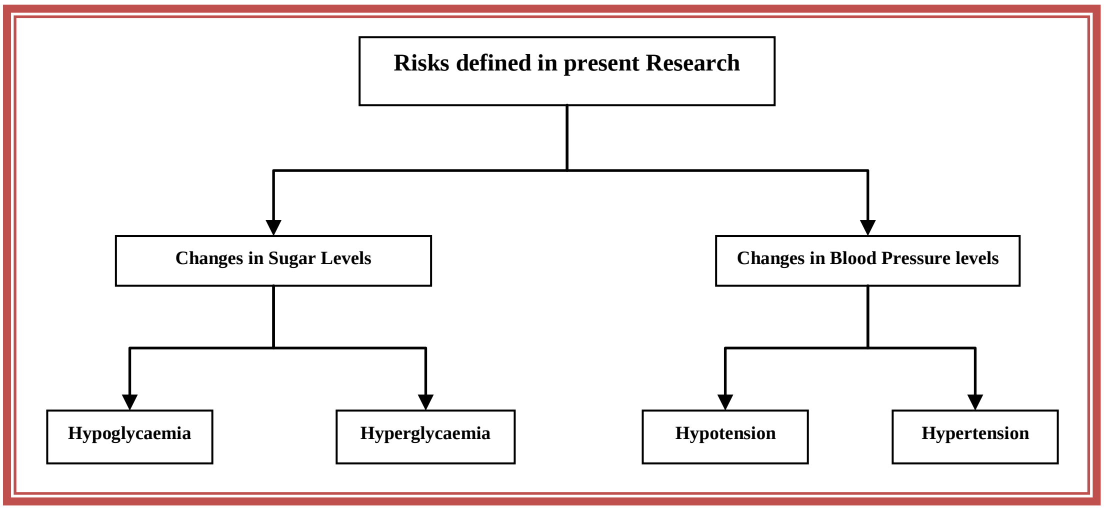


Figure 6: The types of risks in the proposed architecture

3.3. Units of Computation

In a hospital environment, the diabetic patient will have a wide range of facilities which to monitor various health conditions, including equipment measuring blood sugar levels, blood pressure (BP) levels, body temperature, etc. The units of the computational model here include hospital environment, risk prediction component, runtime monitoring, and hospital management team.

3.3.1. Hospital Environment

The hospital environment has been selected for this research. It includes an appropriate range of room temperatures and facilities with measuring devices and monitors to check blood sugar and blood pressure levels constantly. The current research collected the blood sugar and blood pressure levels of 200 patients in the hospital environment for analysing the risk parameters related to diabetic patients. Type 2 diabetes is considered in this research, as it is the type with which most of the patients are affected.

- **Patients**

The patients in this research are affected with type 2 diabetes, as are most affected adults outside the study [82 – 85]. Blood sugar levels are tested for patients in two situations: before and after meals. However, blood pressure levels are measured in terms of high BP and low BP. The normal ranges of these levels in different scenarios are given here with the defined risk labels.

Sugar Levels (Risk Type)	Inputs	In mg/dL
Normal Patient	Before Meals	82 to 110
	After Meals	82 to 140
Low Blood Sugar Levels (**Hypoglycemia**)	Before Meals	50 to 81
	After Meals	60 to 81
High Blood Sugar Levels (**Hyperglycemia**)	Before Meals	111 to 300
	After Meals	141 to 400

Table 1: Defining the risk types with the range of blood sugar values

These values are stored in the database from the monitoring devices in the hospitals after checking patient blood glucose levels. These glucose levels are the inputs for the risk prediction unit. However, any value ranging beyond the values as defined in Table 1 is considered an unknown parameter according to medical standards [85] [97]. These conditions are carefully alerted using the proposed approach. Similarly, patient blood pressure is also considered in the two cases of high and low blood pressure. The corresponding values of blood pressure are shown in Table 2, and values beyond these levels are considered unknown parameters and are alerted to doctors if identified at runtime as a part of the proposed early warning system [98].

Blood Pressure Levels (Risk Type)	**In mm/Hg**
Normal Patient	82 to 110
Low Blood Pressure Levels (**Hypotension**)	50 to 81
High Blood Pressure Levels (**Hypertension**)	111 to 300

Table 2: Defining the risk types with the range of blood pressure values

3.3.2. Risk Prediction Component

In this component, the entire process depends on work functionality of neural networks and the property of neural networks to solve the problem for which the neural networks are trained. This component uses patient blood sugar and BP levels as input values which are then processed through the hidden layers of the neural networks model to predict various risk levels [95]. During this prediction process, the input values are first converted into vector data inputs [28] [96], then applied at the input layer of neural networks. The output values after processing will form an output matrix internally and are converted into neural output values [141 – 145]. These values are diverted to the database after processing in this component.

3.3.3. Runtime Monitoring

Runtime monitoring considers all the actions taken by all the parameters and identifies the status of risk levels by checking with ideal conditions. This component performs all the needful actions (i.e. checking risk levels) for at least mitigating risk values [139] [140]. The database and checker process are the two most important components in the present architecture that work continuously at runtime.

- **Database**

The database collects information on patient BP and blood sugar levels, and these values are applied as inputs for the Risk Prediction Component (RPC). At the same time, the database stores all ideal conditions of normal patient blood sugar levels, BP levels and pre-defined risk levels according to medical standards. These levels are available during the checker operation to compare with the outputs of neural networks.

- **Checker**

The checker will check the outputs of neural networks with the ideal conditions stored in the database. The checker performs this checking process continuously until the specified conditions/risk levels are satisfied. The output of this checker will be stored in the database for the mitigation process.

For example, if the output of the neural networks gives the blood sugar value after meals, the checker will check the database for the ideal conditions that are stored therein. Based on the defined conditions (before meals/after meals) the checker will make a decision before the comparison process takes place. This process will continue until any one of the conditions in the database is satisfied, as shown in Listing 1.

```
rs=st.executeQuery("select * from checker where sno=1");
 if(rs.next()){
ppid=rs.getInt("pid");
beforem=rs.getDouble("beforem");
afterm=rs.getDouble("afterm");
highbp=rs.getDouble("highbp");
lowbp=rs.getDouble("lowbp");
}
```

Listing 1: The code for retrieving the ideal conditions from the database for checker operation

3.4. Communication

The communications between various entities during computations are bound to perform flexibly according to the requirements of the present research. The communication provided among the entities to supply the inputs and outputs of each component according to the interest of adjacent components is shown in Figure 7. This will help the overall architecture to transform the information and data between various parameters and entities. The communication between the database and risk prediction component is of a complex nature due to the involvement of neural networks. However, the resultant output will be consistent, as the process works like a human brain. This in turn also maintains synchronization with the expected values and real values at runtime.

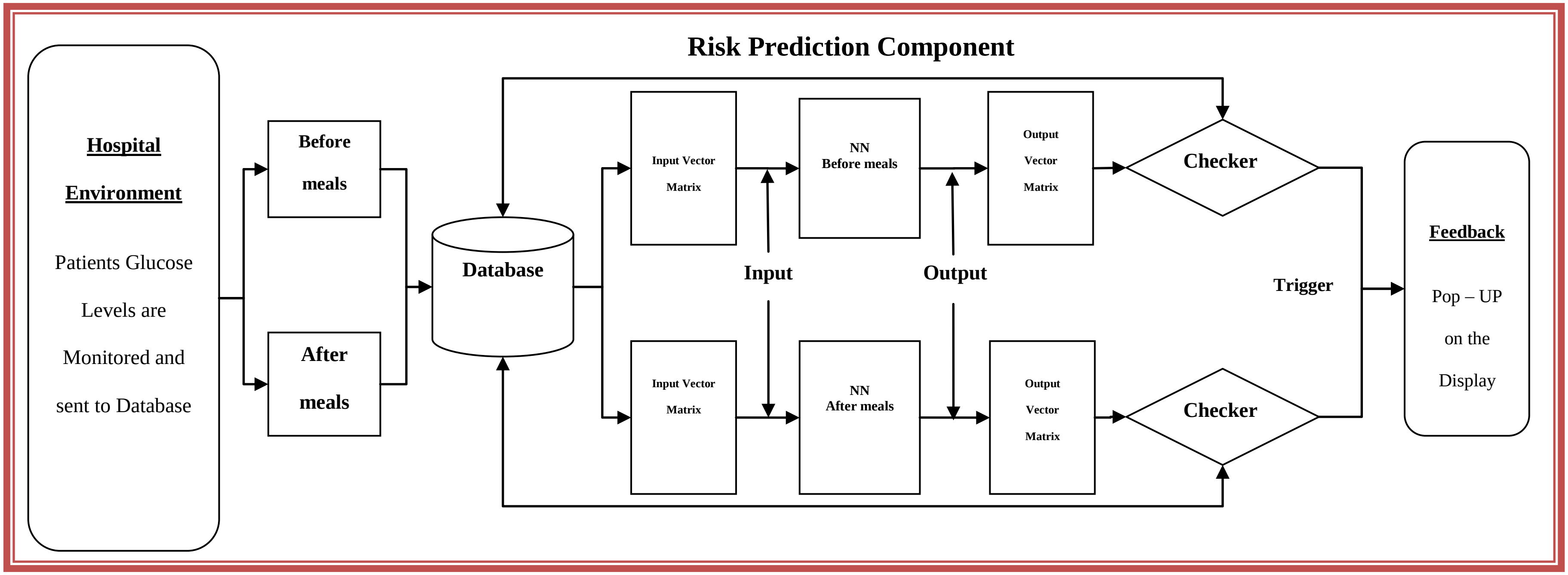


Figure 7: Communication between components of the proposed architecture

3.5. Overview of Neural Networks

Neural networks have solved many complex or intractable problems with efficient results and are used to solve critical, real-life issues. They have been used in radar application, bomb detection and as a controller in many computer games [47]. In this method, mastering neural networks allowed the system to solve various critical problems with ease compared to other methods. Neural networks work on the biological genetic pressures that are applied on the pre-wire forms of natural neural networks. Figure 8 shows the physical structure of a neuron [47].

A neuron is surrounded by thin, hair-like elements known as dendrites. Dendrites enable the activation form of neurons. These dendrites work as terminals allowing input from different sources, and they have certain threshold values. If summations of all incoming dendrites reach the maximum level, neurons burst and the inputs are distributed among the other neurons. The resultant outputs are carried out by the axons, which are thicker and potentially longer than dendrites, to influence the remote neurons. Generally, a neuron is linked with more than ten thousand other neurons [47].

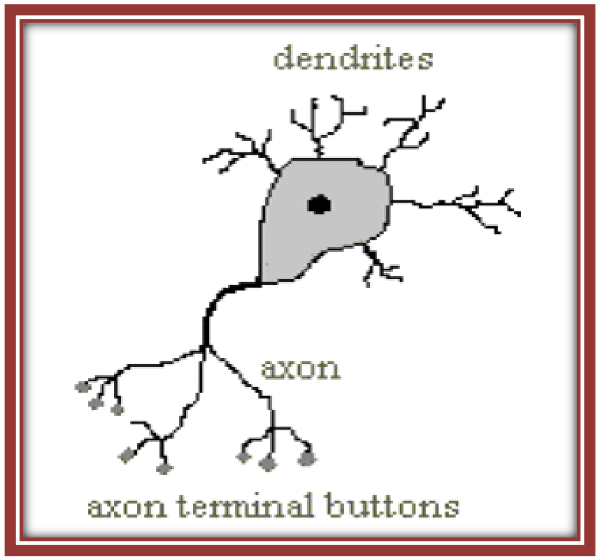


Figure 8: Neuron Physical Structure

The use of neural networks in the medical field has been extensively used in recent times to solve various critical problems, since these neural networks are sophisticated and pattern-learning instruments [48]. Neural networks contain three nodes, as shown in Figure 3.4: input nodes, hidden nodes and output nodes. The two nodes of each edge are associated with a weight and direction of edges, representing the flow of data during the prediction process.

Input nodes generally form the first layer of the network. They are linked with dendrites, and every input node defines a different attribute (such as blood pressure, basal rate, etc. in the present architecture) [47] [48]. The hidden layers are the intermediate layers, receiving input from the input layers or the precedent layers. The role of the hidden layers is to combine all inputs based on the weight of each connected edge, and depends on the process of some calculations. These layers emit the resultant outputs to the subsequent layers, and if the final layers are output layers (axons), the data will be a predicted attribute. Generally, the output of a neural network has multiple output attributes with summed values of several output nodes within the same network lead, reducing processing time and sharing cost by scanning various data sources. The output node results are floating numbers between 0 and 1 [48]. The input nodes in the present architecture (as shown in Figure 9) the values and properties of a input parameters, which are stored in a healthcare database.

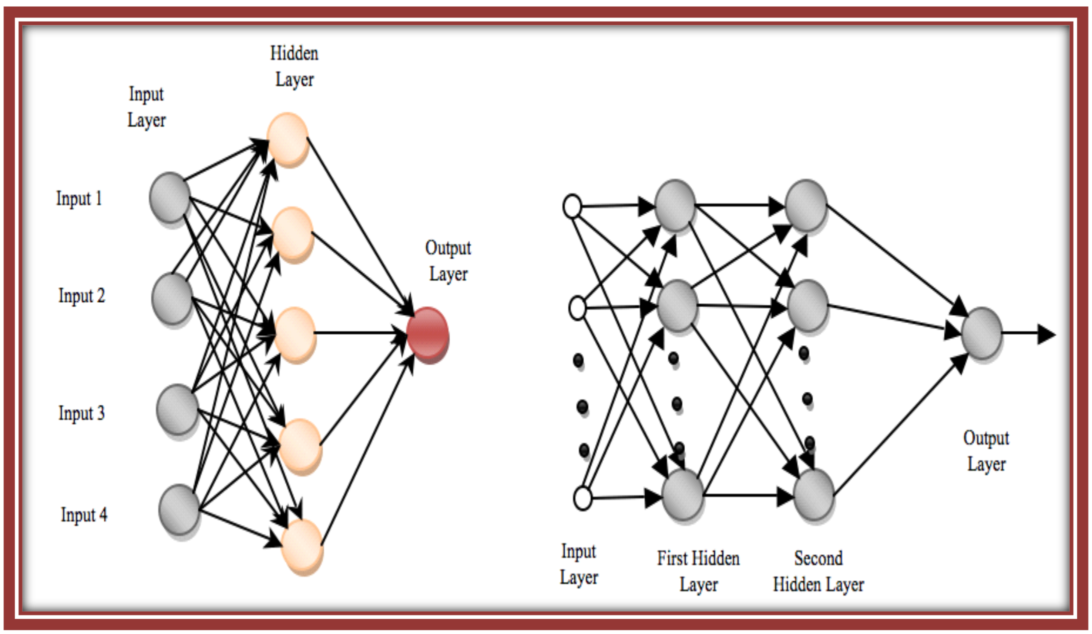


Figure 9: General Architecture of Neural Networks System

3.5.1. Role of Neural Networks in the Proposed Architecture

In the proposed approach, neural networks play a key role in predicting risk levels and unknown parameters. The parameters from the hospital environment are applied at the input and layers of the RPC component are converted into an input vector matrix and compared with the hidden-layer values. The hidden layers are programmed with desired specifications for different inputs (BP and blood sugar values) according to medical standards. The risk prediction components use neural networks to predict the status of input parameters applied at the input. The output values are generated as a vector output matrix, and conversion of this matrix to numerical values takes place internally. These numerical outputs are communicated to the checker component for checking the status of risk levels.

3.5.2. Properties of Neural Networks

There are many neural networks-based systems considered to be more effective due to their non-linear relation among variables. These systems have mostly been learning systems that model the relations between various sets of inputs and set of outputs due to the nature of non-linear relations. These systems are considered black boxes as extracting symbolic information from the internal configuration is difficult. These systems are mechanical learning systems depending on a simplified model of biological neurons [34]. Biological neural networks change their parameters on their own to perform cognitive and computational tasks. The major efficient and effective tasks performed by neural networks were classification, pattern recognition, symptom prediction and cause identification [35]. These neural networks models were also a part of statistics-based scores [36]. However, two main issues always affect applications of neural networks typology: structure and learning algorithm [34].

3.6. Back Propagation Algorithm

There are two types of networks available using neural networks: Hopfield networks and back propagation algorithms. In the first type, the input data only contain input examples. However, in the second type, the data were trained per the desired output patterns along with input patterns. The operation of these two networks is totally different internally, and the first type is very simple to simulate with a program and is widely useful in practical applications as data can be in any dimensions (generally these are in two dimensions) [49]. However, the biggest disadvantage of the Hopfield network is loss of generality by implementing its tool kit with one-dimensional input. Even a two-dimensional image is shown in an equivalent one-dimensional array only.

A back-propagation network model is also known as back-prop and delta rule learning. The neurons in this model are organized in data structures generally called layers. A two-dimensional neural network is shown in Figure 10 with two layers, along with its two-dimensional array and the neuron connections [47]. The neurons are characterised by single floating point numbers with individual weights.

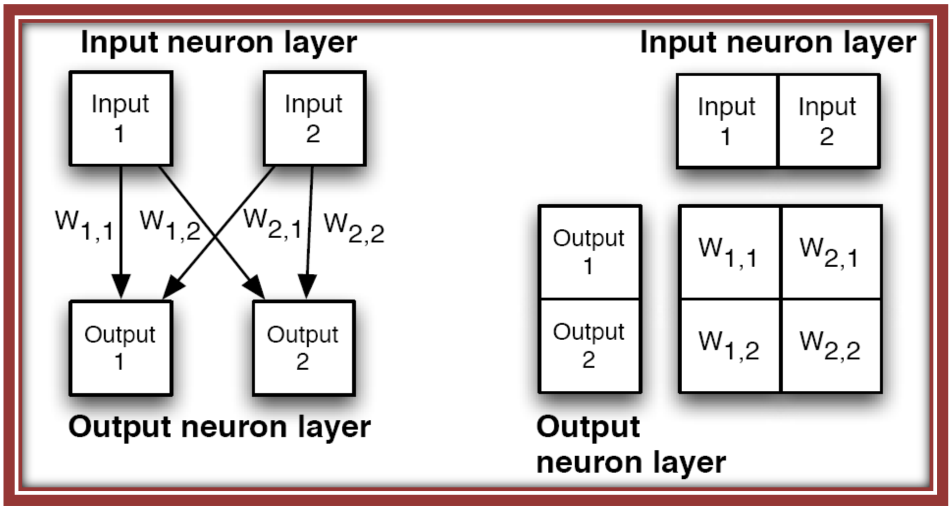


Figure 10: Two-layer neural network in two-dimensional array in two different methods

The important reason for using a back-propagation (also known as back-prop [47]) algorithm is that it is a supervised learning algorithm. It is used for multi-layer perceptions to change respected weights connected with the total hidden neuron layers [50]. This algorithm used the computed output errors to change the weight values in a backwards direction. For retrieving the total error, forward propagation was done earlier. During forward propagation, the neurons would be activated using a sigmoid activation function as shown below [50]:

$$f(x) = \frac{1}{(1+\exp^{-\text{input}})} \quad ....3.1$$

The back propagation algorithm worked based on the following four steps [50]:

- A forward propagation phase with respect to the input pattern was performed and error output calculated.

- All weight values of each weight matrix were changed using the formulae.
- Step 1 was repeated.
- This algorithm process ended once all the output patterns matched their target patterns.

In Figure 10, two neuron layers are shown for input and output neurons. The first and second output neuron (O1 and O2) were calculated using the following equations for a sigmoid activation function:

$$\mathrm{O1} = \mathrm{Sigmoid}(\mathrm{I1} * \mathrm{W}[1,1] + \mathrm{I2} * \mathrm{W}[2,1]) \quad \ldots 2.2$$

$$\mathrm{O2} = \mathrm{Sigmoid}(\mathrm{I2} * \mathrm{W}[1,2] + \mathrm{I2} * \mathrm{W}[2,2]) \quad \ldots 2.3$$

A plot can be drawn between the sigmoid function and derivative of the sigmoid function (SigmoidP).

3.6.1. Deep Belief Networks (DBN)

These networks are used when the number of hidden layers is supposed to be increased due to the rise in input parameters. Neural networks are treated as feed forward neural networks also called deep neural networks (DNN). DBN have undirected connections between layers [51] [66]. These layers can be trained using unsupervised learning algorithms, which are very fast. However, these neural networks perform worst when the hidden layers are more than one or two while performing for faster responses. Deep belief networks have the following advantages over neural networks [51]:

- Learning algorithms are faster and greedier, establishing a good set of parameters more quickly to a very deep extent [67].
- Though the learning algorithm is unsupervised, it can still be applied to label the data by learning models that generate both labels and data [68].
- Generative models make interpretations in a distributed representation within the deep hidden layers [69].
- The interference needed to format the precept is much faster and more accurate in forming the fast-acting layers.

Though the DBN can perform excellently in a maximum number of hidden layers, the use of these networks is limited because hidden layers must be trained faster and data learning must be performed at a faster rate. However, in using neural networks these problems will not exist and, moreover, due to advancement in technology the NN are also providing accurate results at around 90%, as discussed in section 2.5.2.

3.7. Summary

A computational model was presented to design the early risk warning system approach. Different units of computation were discussed including the risk prediction component, runtime monitoring, hospital management team and environment. The use of neural networks and its advantages over other methods was also summarised in this chapter. In the next chapter, the architecture of the proposed approach using Java and neural networks will be discussed.

Chapter 4: Architecture

Objectives

- To provide the system architecture and its overview
- To illustrate the architecture components
- To provide the interactions between each component of the architecture
- To describe the different functions and components

4.1. Introduction

The aim of this chapter is to provide the proposed architecture of the ERWS approach. A brief summary and explanation of how the architecture works is given in section 4.2. The environment used for this research is explained in section 4.3 with the information of patients and different monitoring devices used in the hospital environment. Section 4.4 explains the risk prediction component and its needs in our model. The components of runtime monitoring are explained in section 4.5, in which database, checker and mitigation processes are explained in detail. The role of the hospital management team is explained in section 4.6, followed by the interaction of components in section 4.7 to explain the communication between different components.

4.2. Overview of the Architecture

In healthcare centres, risk management is implemented for a statistical system in which risk mitigation is performed only after the damage has occurred. This method compromises the life of patients due to the delay in risk occurrence and solution provision after a delayed mitigation process. Timely feedback to doctors and patients about the tentative risk levels of a diabetic patient in real life will help both patients and doctors to be alert to the health condition of a patient.

There are various risks identified in diabetic patients due to an increase/decrease in blood sugar and blood pressure levels. In the case of blood sugar levels, the risks identified are termed as hyperglycaemia (for high sugar levels) and hypoglycaemia (for low sugar levels). These two risk parameters generally vary in a patient before and after meals. A patient sometimes enters a critical condition when blood sugar values extend past certain limits. In such situations, patients even risk loss of consciousness or death.

In the case of BP levels, there are two risk levels defined according to medical standards as hypertension/ Systolic (high BP levels) and hypotension/ Diastolic (low BP levels) [98] [123]. Different risk conditions associated with BP levels are shown in Figure 11. The possibility of death is greater in a situation where high BP levels extend below 50 mm/Hg and above 240 mm/Hg. Death is also possible where low BP levels extend below 30 mm/Hg and above 130 mm/Hg, as shown in Figure 11.

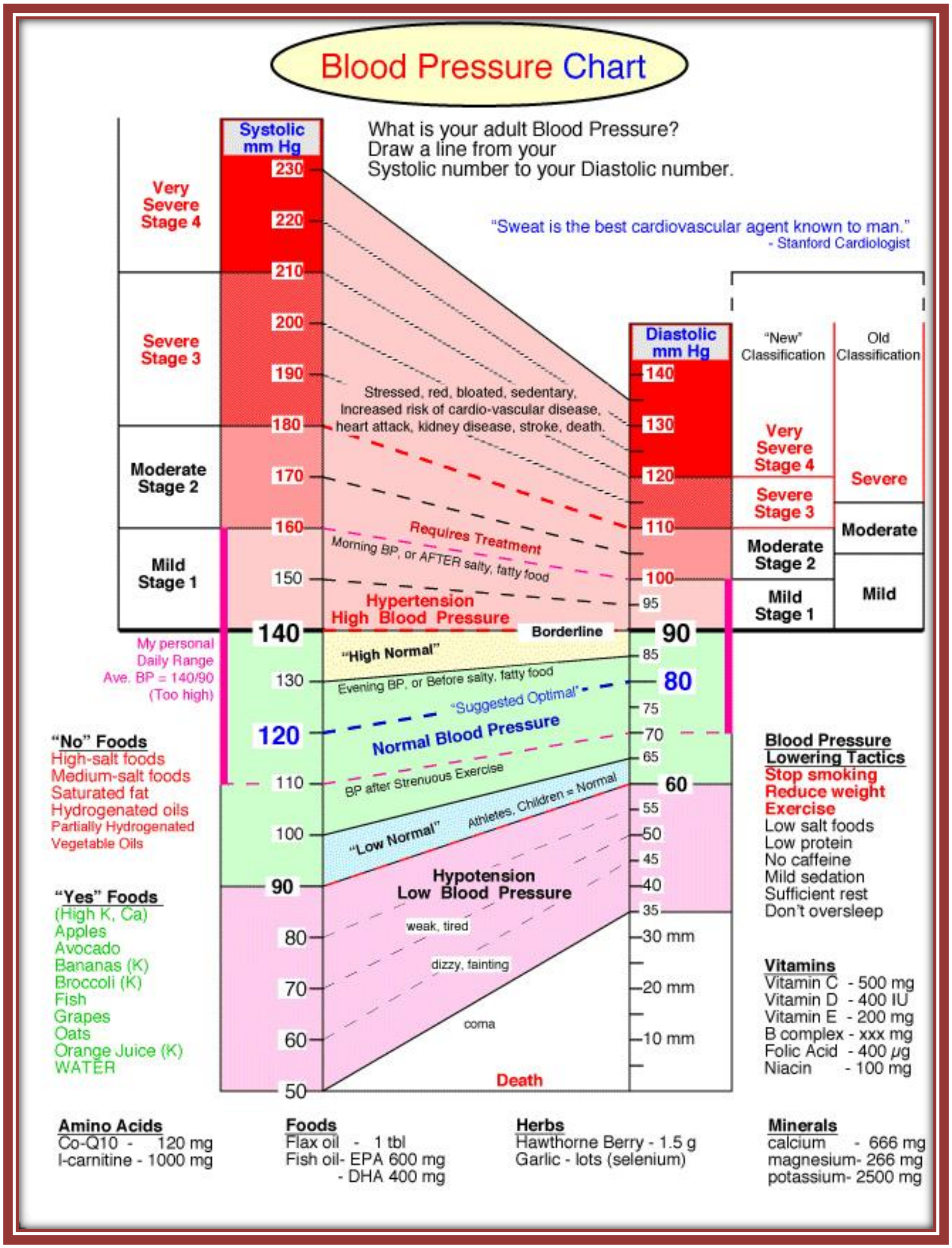


Figure 11: Different risk conditions related to BP conditions

The current risk management system does not have sufficient resources to solve most of the problems in the healthcare [44] as per a report generated by the US Department of Health and Human Services. The increase in medical products and their applications leads to many complex situations. Sometimes even physicians are not in touch with the flow of new products due to their time constraints dealing with various patients due to increased risk parameters at runtime. These risk parameters reach beyond the scope of a physician in healthcare [44].

This research covers multiple areas to identify risks by developing an early risk warning system for possible risks at runtime. However, risk management techniques in software engineering focus only on software development projects in the early years of the last century. These techniques were used with different ad hoc approaches without following any systematic methodology [52]. However, at runtime there will not be any kind of limitations for the increase in risk parameters, as they tend to change or increase. If these risk parameters are not identified in early stages, they tend to become a serious problem in the near future.

Runtime monitoring plays a key role in checking patient health conditions continuously and detecting possible levels of risk parameters. This will overcome the problems faced by the current risk management system in healthcare, which does not provide the best possible solutions [53]. In addition, runtime monitoring in this architecture will allow ample time for doctors and management teams to mitigate new problems with ease compared to the traditional method in which problems are solved after damage occurs.

This research proposes an early risk warning system approach for the hospital environment to satisfy the needs of a diabetic patient. Our approach is to predict and check the blood glucose and BP levels of a patient on a regular basis. These levels are stored in the database and processed through the risk prediction unit. In the risk prediction unit, neural networks will compare the input values with hidden layer values and provide the suitable output level. These neural output values are compared with the ideal risk levels that are already defined in the database. This checker process continues until patient health condition status is predicted. Once these values satisfy any of the risk or no-risk levels, the trigger operation takes place to alert/communicate with the patient and doctors with the relevant predicted results. Based on these alerts, the healthcare management mitigates and proposes possible recommendations for unknown parameters. Therefore, the key aspects of our approach are:

- How to enter the monitored BP and blood sugar level values of a patient into a database as an input for the risk prediction component.
- How to train the hidden layers and define the appropriate weights and momentum in the hidden layers in the risk prediction component.
- How to check the BP and blood sugar levels of patients with ideal conditions and identify patient health status (with risk or no risk or unknown parameter).
- How to communicate interactions between various components and generate alerts for doctors and patients at regular time intervals.

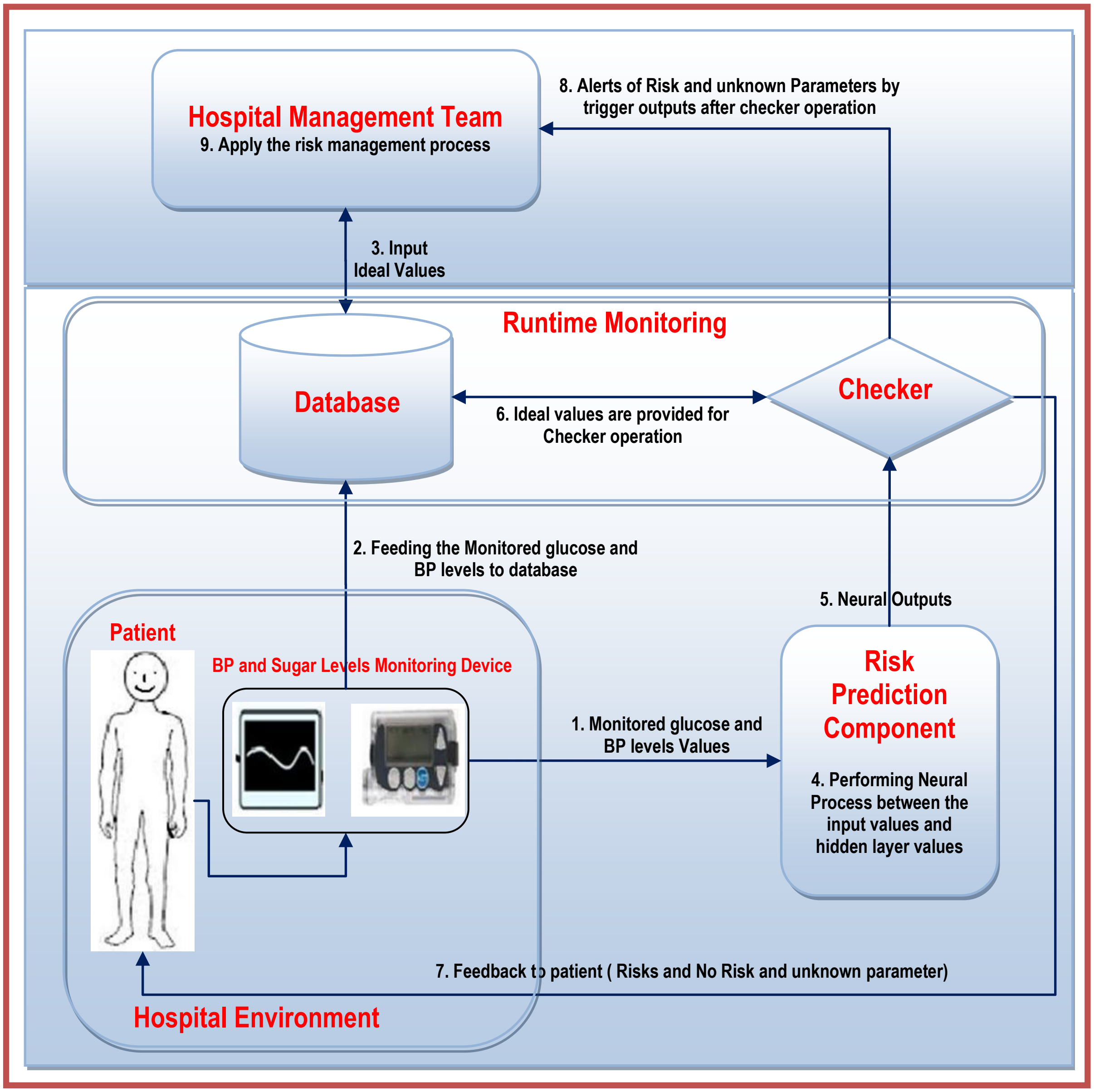


Figure 12: System Architecture

Based on the above aspects, the architecture is classified into four components: Hospital Environment, Risk Prediction, Runtime Monitoring and Healthcare Management.

4.3. Hospital Environment

The hospital environment for this research is the Al-ANSAR Hospital in Saudi Arabia. In this hospital, much research is being conducted on diabetic patients, and it is equipped with good laboratory facilities for new research activities. The hospital environment is entirely air-conditioned, hence the room temperatures will be considered normal. In the meantime, the research and interaction with various experts and doctors in the hospital revealed that the body temperature of a diabetic patient will not be greatly affected by the changes in patient blood sugar or blood pressure levels. The key entities in the proposed architecture are patients and BP and blood sugar levels monitoring devices, as shown in Figure 12.

4.3.1. Patients

The research considered and collected information from 200 patients according to the suggestion of the experts/doctors at Al-ANSAR Hospital. This information was collected with suitable terms and conditions according to hospital rules to be used only for this research purpose. The parameters provided by the hospital include blood sugar levels of patients before and after meals and blood pressure values for each patient. These values are for patients suffering from type 2 diabetes according to doctors' records. Most of the diabetic patients were found to be suffering from type 2 (rather than type 1) diabetes.

The blood sugar and BP levels of the patients were collected from Al-ANSAR hospital and a sample of ten patients' information is provided here with different conditions.

The blood sugar levels of patients were collected before and after meals. The blood sugar and BP levels collected were of patients visiting the hospital, and these values were collected from October 2012 to July 2013.

4.3.2. Blood Sugar Level and Blood Pressure Level Monitoring Devices

The monitoring devices measure the values of patients' blood sugar and BP levels in the hospital environment. These levels are communicated with the database for further assessment of patient conditions using the proposed approach [132 – 134]. However, in the present research the values were acquired from the medical reports of the patients and these values were stored in the database to implement our proposed architecture. At runtime, these values will be updated in the database at regular intervals and will be available at the input of the risk prediction component. Patient names are not mentioned but are represented with a sequence of Patient ID (PID) numbers. In this implementation we used PID numbers from 101 – 110 as shown in Tables 3 to 6. For health details of all 200 patients see Appendix D.

BLOOD SUGAR LEVELS

	October	November	December	January	February	March	April	May	June	July
101	85	70	77	80	80	79	81	86	90	102
102	109	185	76	98	75	86	78	90	160	115
103	110	100	79	96	80	98	75	79	76	119
104	111	80	96	80	100	99	88	96	102	90
105	111	102	95	97	84	86	81	88	90	92
106	118	125	86	98	87	89	87	94	90	85
107	115	119	87	98	94	88	80	81	83	80
108	85	70	77	80	80	79	81	86	90	102
109	86	81	79	80	88	79	82	75	84	83
110	120	104	116	99	87	80	77	79	72	85

Table 3: Blood sugar levels before meals of 10 patients according to hospital records

	October	November	December	January	February	March	April	May	June	July
101	152	246	147	242	174	124	92	142	193	225
102	165	170	140	250	195	164	188	320	160	115
103	152	289	257	242	198	152	166	142	193	225
104	147	159	150	180	169	200	160	157	166	149
105	200	192	219	152	160	140	160	149	169	179
106	225	250	146	150	149	166	192	140	160	111
107	246	199	152	160	159	135	146	149	151	163
108	155	159	165	138	170	159	157	164	152	171
109	170	159	162	148	164	169	155	164	158	146
110	356	299	268	189	160	159	157	145	159	188

Table 4: Blood sugar levels after meals of 10 patients according to hospital records

BLOOD PRESSURE LEVELS

	October	November	December	January	February	March	April	May	June	July
101	80	82	70	82	90	82	90	79	80	77
102	82	79	82	79	80	79	80	80	82	83
103	79	88	79	88	80	88	82	84	79	80
104	88	82	88	75	82	75	79	80	80	89
105	75	79	75	75	79	88	85	88	86	83
106	82	88	80	79	88	75	78	79	79	80
107	79	82	82	82	82	79	79	88	88	82
108	88	79	79	79	79	88	82	75	75	79
109	75	88	82	88	88	75	79	80	82	88
110	80	75	79	82	76	75	88	78	80	79

Table 5: Low blood pressure levels of 10 patients according to hospital records

	October	November	December	January	February	March	April	May	June	July
101	120	140	154	140	151	140	164	142	125	124
102	140	135	140	135	144	135	120	125	140	135
103	135	150	135	150	120	150	140	147	135	125
104	150	140	150	119	140	119	135	120	120	126
105	119	135	119	150	135	150	154	144	140	135
106	140	150	120	135	150	119	128	135	139	120
107	135	162	148	140	138	135	130	145	150	140
108	150	135	135	135	135	150	140	119	119	135
109	119	150	140	150	150	119	135	129	138	150
110	123	119	135	140	124	145	150	130	136	127

Table 6: High blood pressure levels of 10 patients according to hospital records

4.4. Risk Prediction Component

The risk prediction component (RPC) retrieves the inputs from the stored values of the database (BP and blood sugar levels from the hospital environment). These values are converted into an input vector matrix and are applied to the input of neural networks. In neural networks, the hidden layer weights and random values are defined with random values. The back propagation algorithm is used to calculate these hidden layer values in different predefined layers.

The input matrix appearing at the input of NN is compared against the values in the hidden layers [55] [56], and resultant outputs are provided as input for the checker. However, in the output of neural networks, the values will be formed into an output vector matrix, and these values are converted into equivalent numerical values before the checker operation takes place, as shown in Figure 13.

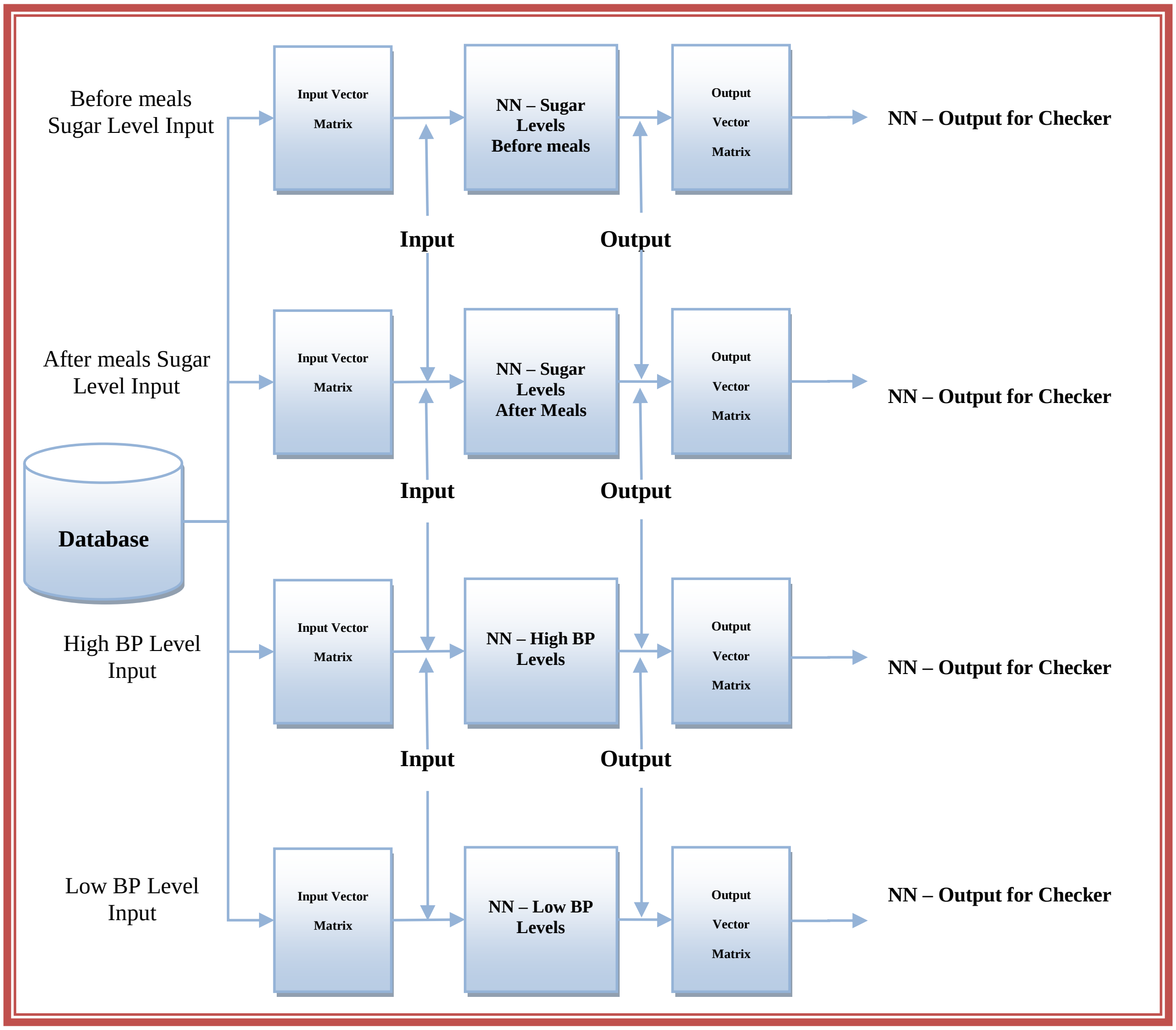


Figure 13: The Layers of NN in RPC for different input parameters

4.5. Runtime Monitoring

The healthcare industry is mostly working with a static environment [57] [58], where the process of risk mitigation tends to happen only after the damage is incurred. Identifying risks is essential for a healthcare operation to avoid possible risks in the near future. Runtime monitoring aims to provide continuous checking [146] [148] of patient health conditions to identify changes in various parameters (i.e. blood glucose and BP levels).

Runtime monitoring (as shown in Figure 14) in the present research provides detailed information of the activities happening related to patients in the hospital environment. In our architecture, the main component of runtime monitoring is the checker component. Runtime monitoring will collect patient information from the hospital environment component, such as blood sugar and BP levels, store this information in the database and on demand provide suitable information for a continuous checker operation [59] [60].

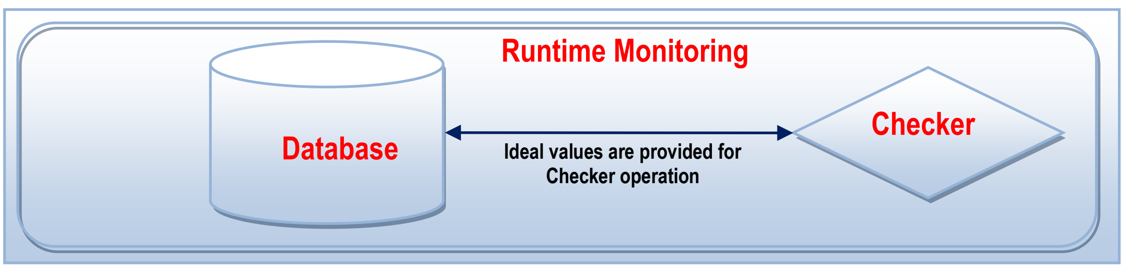


Figure 14: The Runtime Monitoring Component

4.5.1. Database

The database in this proposed architecture interacts with various input and output components to collect and store information. On demand it will provide the desired inputs (i.e. BP and blood sugar levels as shown in Tables 3 to 6) for various components to process the values assessing health conditions of various patients [137]. The database will work as an intermediary between various components to interact with, retrieve and store information according to the needs of different applications.

The design of the database was based on MySQL applications for simplicity and faster operation compared to other methods of database design using Oracle and SQL.

4.5.2. Checker

The checker in our architecture checks the executed results obtained by the RPC with the ideal conditions stored in the database. This identifies the status of patient health conditions [61 – 64] and finds the range of parameters where the patient's health condition is suitable or matching. Based on satisfactory results the checker component decides [65] [136] to provide feedback to the patient and healthcare team management. For example: assume that a patient's blood sugar levels are increasing rapidly with respect to time.

The checker first blood sugar levels against standard conditions defined according to medical standards. If any of the glucose levels are within the range of hyperglycaemia (i.e. if the blood sugar levels are increasing rapidly), the checker will give feedback [149] to the patient and healthcare management through the database after satisfactory checking with that condition. Otherwise, the checker will check for other conditions, as shown in Figure 34. Assertion techniques are used to test the possible conditions that are defined or not. If none of the defined conditions are satisfied, the checker declares the status [150] as an unknown parameter. Chapter 5 describes how the checker checks the patient health condition at different risk levels.

4.5.3. Mitigation

In this research, the mitigation process plays a key role, as it is related to patient health conditions and life. Mitigation reduces the probability of serious health problems to avoid serious damage. Our architecture tests the sugar and BP levels of patients using RPC. The output of RPC is checked and the resultant feedback is given to the team management component. Doctors and analysts will check for the newly identified parameters and propose solutions for tentative problems after mitigating with previous conditions and overcoming the risk levels tending to occur in near future [134] [135]. Triggers are applied when a patient’s health condition is reaching serious risk levels. These levels are communicated by alerts to initiate doctors and patients to take necessary precautions.

In our architecture, mitigation includes suggestions for the patients from various medical reports, and the patient is advised according to those guidelines for different risk levels. For example: a patient identified with hyperglycaemia is advised to maintain a good diet, healthy food habits and regular exercise, and to reduce the content of sugar in his/her diet. These suggestions change based on observed blood glucose levels. The process of mitigation will be based on the checker outputs in this architecture. Chapter 7 describes how mitigation is done by sending feedback on patient health condition at different risk levels.

4.6. Hospital Management Team Component

This unit contains the hospital management along with experts and analysts to make decisions based on identified risk. They compared the previous data with the present data, analyse the criticality of the identified risk and propose improved solutions by updating the database. The role of healthcare units will be very important in making decisions in a runtime environment. The performance of this unit will be especially critical in situations like natural disasters and accidents, as the number of risks identified by the runtime monitoring system will be greater compared to other normal conditions.

4.7. Interaction Component

This component explains the interaction between multiple components to drive the focus of proposed research in an easy way. This explains the programmer, the flow process of the proposed approach and the communications. The sequence diagram for the interactions between each component is shown in Figure 15.

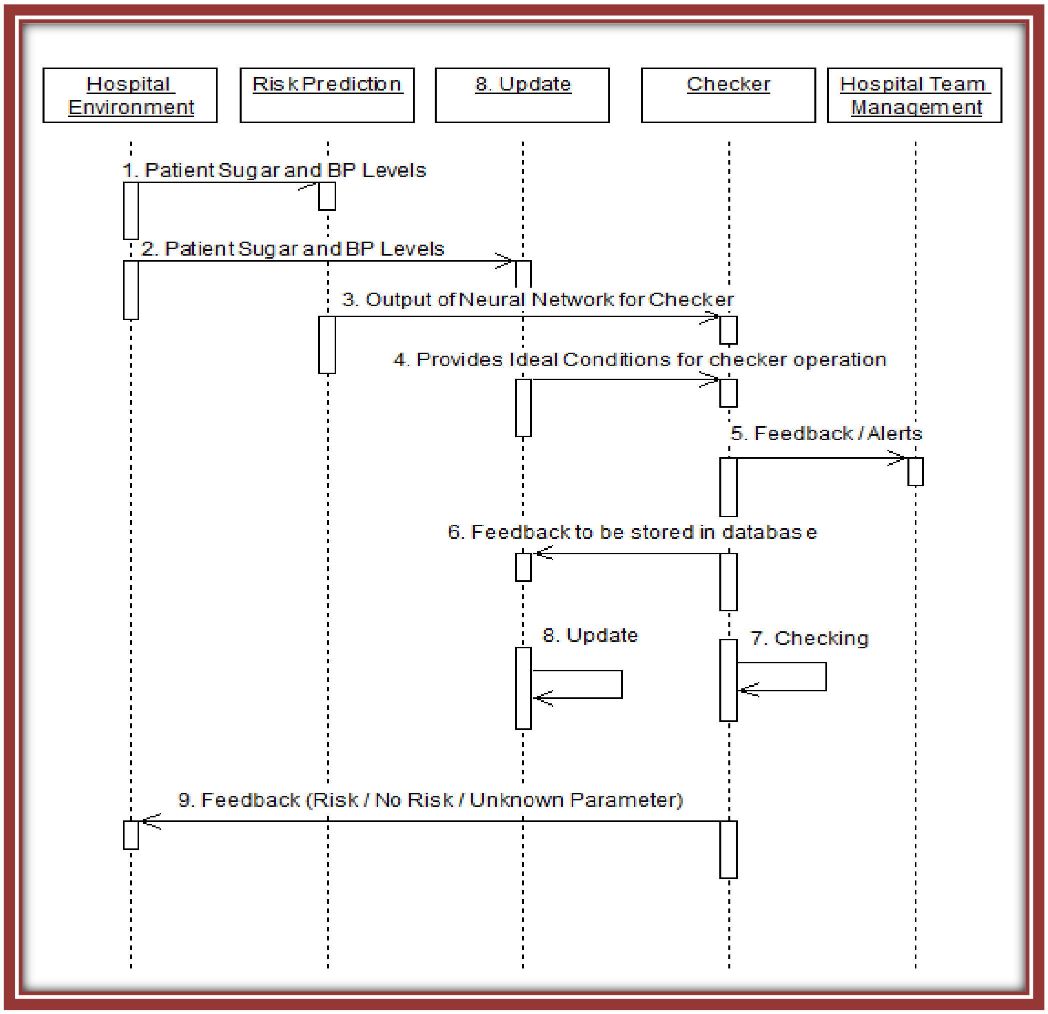


Figure 15: Sequence diagram with component interactions

4.8. Summary

The architecture of the proposed approach was illustrated and detailed descriptions of each component were provided. This architecture contains the hospital environment, risk prediction component, runtime monitoring and hospital management team. All components were explained in detail along with their functionalities. Using the sequence diagrams, the interactions were explained between different components.

Chapter 5: Risk Prediction and Runtime Monitoring

Objectives

- To describe the risk prediction component and functionality
- To show the risk prediction algorithm in the proposed architecture
- To describe the runtime monitoring functionality
- To illustrate the interaction between risk prediction and runtime monitoring

5.1. Introduction

In this chapter, the risk prediction and runtime monitoring components of the proposed approach are discussed with the suitable implementation process. The functionality of the risk prediction component and its implementation steps are discussed in section 5.2. The neural networks-based prediction algorithm and its implementation steps using Java language are discussed in section 5.3. The analysis of the back propagation algorithm for different neurons is explained in section 5.4. The implementation of the runtime monitoring system and checker operation are explained section 5.5.

5.2. Functionality of the Risk Prediction Component

Various activities took place in this component towards predicting risk levels. All these actions happened with the help of neural networks in the risk prediction component. The blood sugar and BP levels stored in the database are applied to the RPC as inputs, which are converted to an input vector matrix, as shown in Figure 13. The size of the matrix depends on the risk parameters applied at the input [48]. The values in the input matrix will be compared with the hidden layer values and weights (defined by back propagation) [71 – 73], and a corresponding output vector matrix will be delivered.

5.2.1. Risk Prediction Component

This component predicts changes in the parameters (blood sugar and BP levels) for the healthcare industry. The functionality of this component is based on the principles of neural networks to identify the current status of the input variables collected from patients' health status [136] [138]. The inputs from the hospital environment were converted into a data matrix and were compared with the values stored in the hidden layers. Based on the training values to the neurons and system specifications the risk levels were predicted using this risk prediction component (see Figure 16).

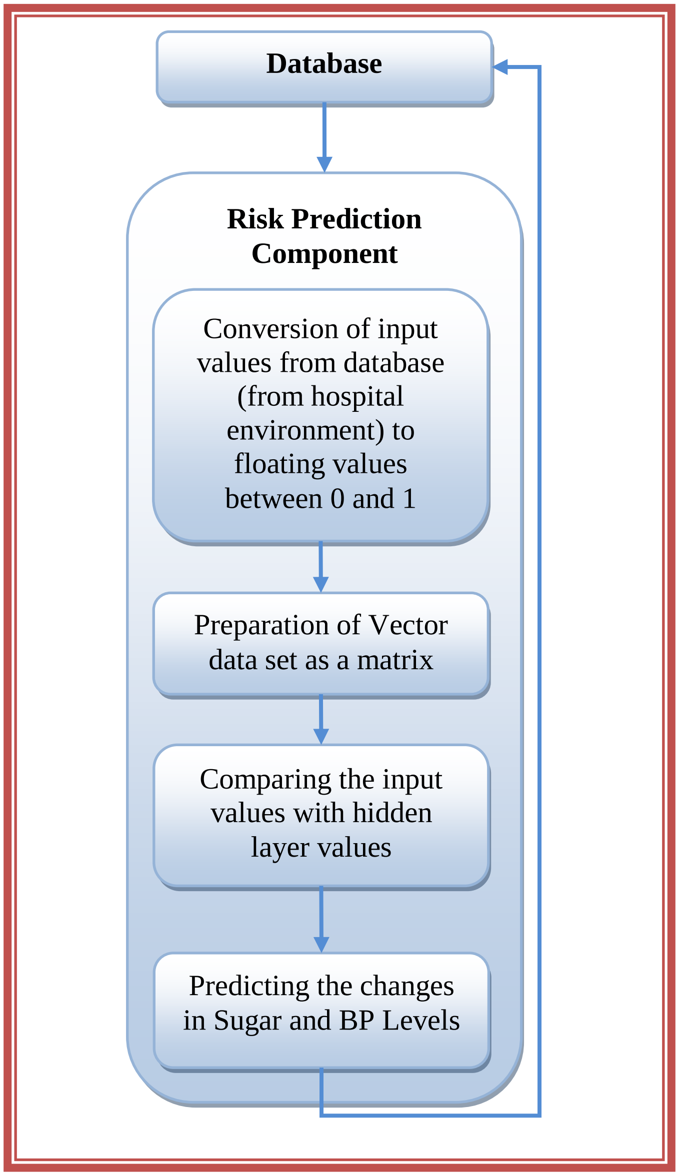


Figure 16: Functions of Risk Prediction Component

After this, a matrix comparison was made based on the values stored in the hidden layers. These predicted parameter values were again communicated to the database for the checker component.

5.3. Neural Networks and Prediction Algorithm

The back propagation algorithm is used to compare and assess risk levels. The major advantage of using neural networks is its ability to perform tasks based on training data, i.e. adaptive learning [73]. Apart from that, it also organizes itself with the received information during the learning time, and hence is more suitable for real-time operations. The tolerance towards finding faults is very high and retains the major information that is damaged very quickly [73].

5.3.1. Transfer Function and Behaviour of Neural Networks

The entire behaviour of neural networks depends on weights and input-output functions as specified for different units. These functions are generally categorized into three types: linear, threshold and sigmoid functions. In a **linear function** the output is proportional to total output weights. In a **threshold function** outputs are defined at two levels based on total inputs as greater than or less than some defined value [73]. In a **sigmoid function** the output varies continuously. However, this variation is linear, as the inputs were changing every time. These sigmoid units were at greater similarity to real neurons when compared with linear or threshold functions and units.

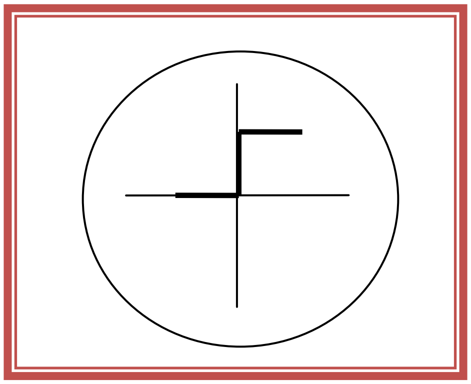


Figure 17: The Step Function (Step(x) =1, if x ≥ 0; x < 0)

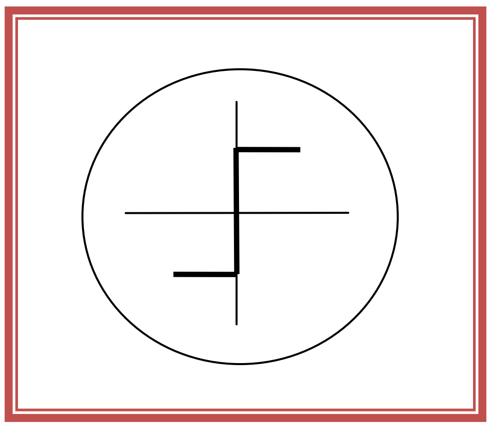


Figure 18: The Sign Function (Sign(x) = +1, if x ≥ 0; Sign(x) = -1, if x < 0)

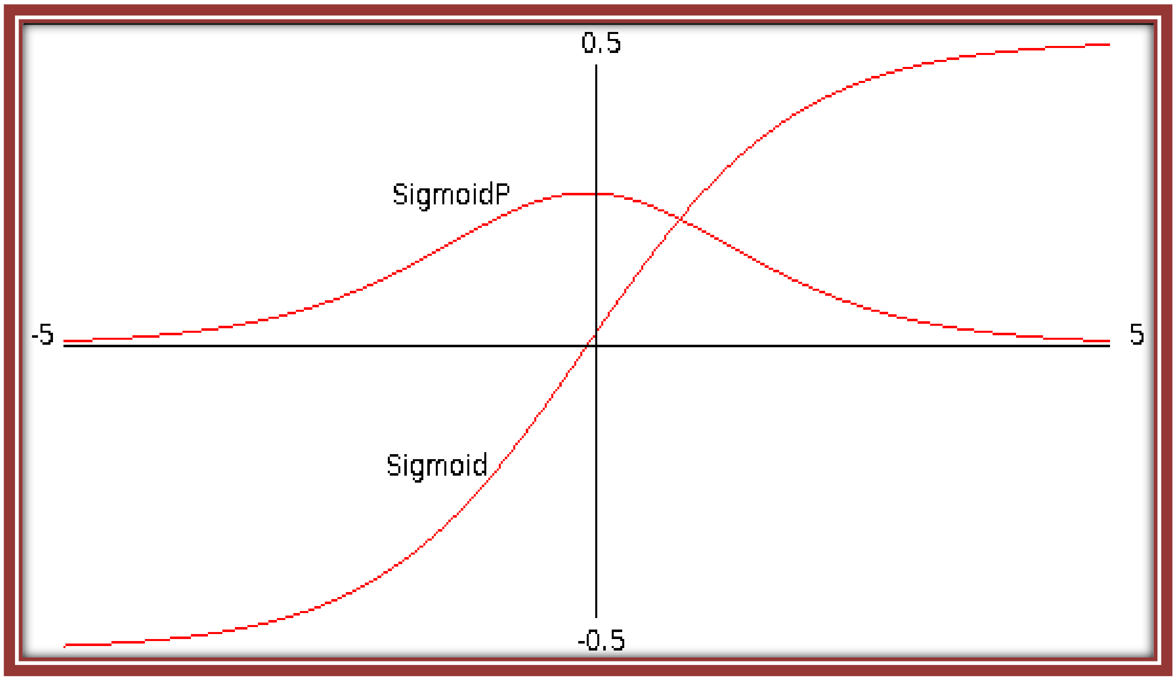


Figure 19: Sigmoid and derivative of the Sigmoid (SigmoidP) functions

$$Where\ \ldots \left(\mathrm{Sigmoid(x)}\ = \frac{1}{(1+e^{-x})}\right)$$

In the case of neural networks, a specific task is to choose how the units are interlinked and the weights set to an approximate value. The interlinking connections identify whether a unit is influencing another neuron or not [73].

5.3.2. Risk Prediction Algorithm

In this research, a back propagation algorithm is used as the prediction algorithm using neural networks. It uses feed forward topology, supervised learning and back propagation learning. It is a powerful algorithm, and is also considered an expensive method due to the requirement of heavy training. Another major advantage of using a back propagation algorithm is to add momentum for making the learning process faster, increasing the chances of predicting difficult problems [48].

The role of the back propagation algorithm in this component is performing three main functions, shown in Figure 16.

- Input patterns were applied at the input layer of the neural network. These inputs were propagated using neural networks until they reached outputs. This is how the forward pass generated actual or predicted pattern of output [73].
- Outputs were generated as a training vector since the algorithm used here was a supervised learning algorithm. The error signal (risk parameter in the current research) was the result of subtraction between actual network outputs and desired outputs.

These error signals were passed to hidden layers, and corresponding adjustments were made to get the desired output. The formula for **sigmoid activation** is:

$$f(x) = \frac{1}{(1+exp^{-input})}$$

The algorithm works as follows [50]:

1. The forward propagation phase with respect to the input pattern is performed and error output calculated.
2. All weight values of each weight matrix are changed using the formulae.
3. $Values\ of\ weight\ matrix = Weigh\ (old) + \ Learning\ Rate \times output\ error\ \times output\ (neurons\ i) \times Output\ (neurons\ i+1) \times (1 - Output\ (neurons\ i+1))$
4. Step 1 is repeated.

This algorithm ends once all the out patterns match their target patterns.

5.3.3. Analysis of Back Propagation Algorithm for a Neuron J

The present conditions of patient details were applied at the inputs. The desired output $e_j(n)$ was the overall result of different hidden layers, as shown in equation 5.1. However, the output of neural networks can be a numeric value, and sometimes the value of a simple summation like 2 + 2 can be 4, or even 3.8 based on the overall average values at different hidden layers. However, the behaviour of outputs of neural networks is correct in most situations, and the processing time also is very fast. Hence, the desired output is expressed as shown below [74]:

$$e_j(n) = d_j(n) - y_j(n) \text{ .... } 5.1$$

$\boldsymbol{e_j(n)}$ - Desired output

$\boldsymbol{y_j(n)}$ - Actual output

Considering j as hidden-layer neuron and k as output neuron, the signal flow graph for different layers in neural networks is shown in Figure 20. However, the instantaneous error value of error energy can be identified using equation 5.2.

$$E(n) = \frac{1}{2}\sum_{j\in c} e_j^2(n) \text{ .... } 5.2$$

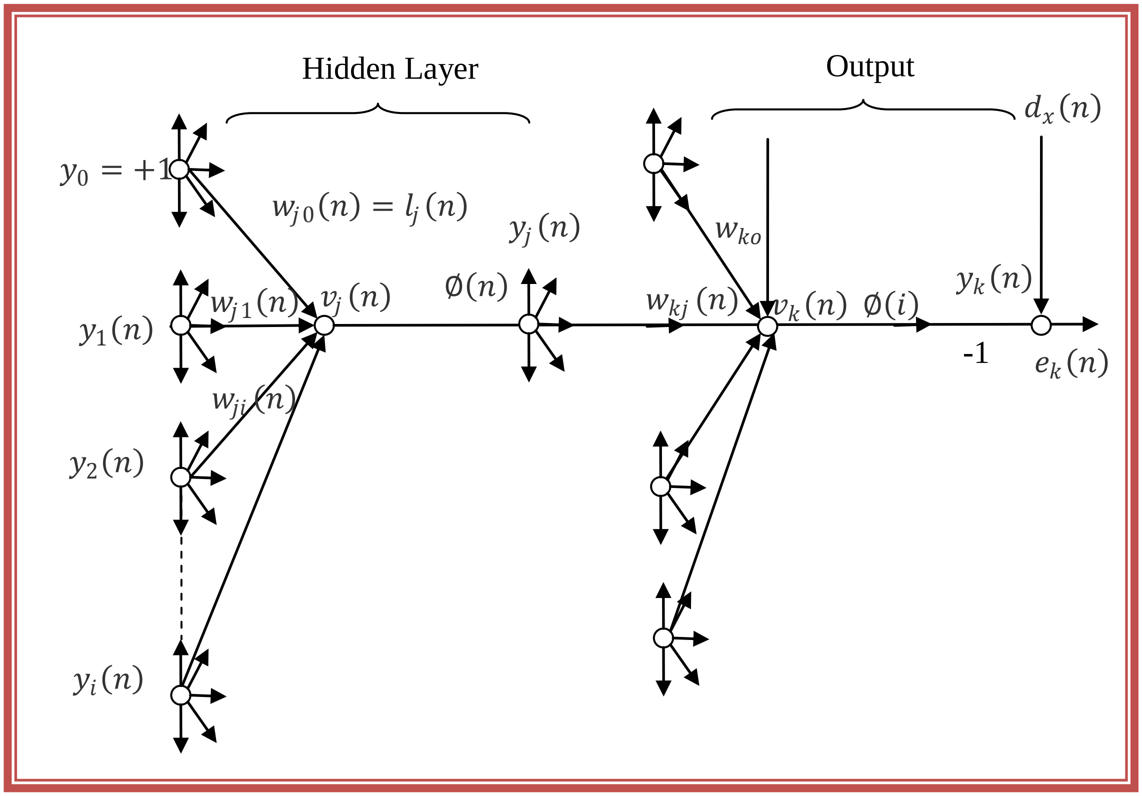


Figure 20: Signal flow graph of different layers in neural networks

These error values define the levels of different parameters at runtime to predict risk levels. However, the total actual output depends on the average square energy of the different hidden layers in the neural networks, and is given in equation 5.3 for N number of patterns.

$$E_{avg}(n) = \frac{1}{n}\sum_{n=1}^{N} E(n) \text{ .... } 5.3$$

N – Number of patterns

Induced local field at the input of neuron j can be calculated using equation 5.4 to calculate the strength of the parameter for M number of neurons. The actual output $y_j(n)$ as the response of overall activation function is given in equation 5.5.

$$v_j(n) = \sum_{i=0}^{m} w_{ji}(n) y_i(n) \text{ .... } 5.4$$

M – Number of neurons

$$y_j(n) = \emptyset(v_j(n)) \text{ .... } 5.5$$

$\emptyset$ – Activation function

Based on these functions, the error values could be identified at different layers and the monitored risk values were displayed using Java programming. The output value was calculated based on the firing rules of neural networks, which are known for their higher flexibility. This firing rule determines calculation of whether a neuron must be fired on not for a set of input patterns [73]. This firing rule can be implemented by a Hamming distance technique. By considering a node with a set of training patterns, the output was based on the nearest pattern value. The truth table shown below explains how the firing rule is applied in neural networks.

X1	0	0	0	0	1	1	1	1
X2	0	0	1	1	0	0	1	1
X3	0	1	0	1	0	1	0	1
OUTPUT	0	0	0/1	0/1	0/1	1	0/1	1

Table 7: Truth table before applying firing rule in neural networks

After applying the firing rule, the output in every column changes and the truth table appears as shown in Table 5.2.

X1	0	0	0	0	1	1	1	1
X2	0	0	1	1	0	0	1	1
X3	0	1	0	1	0	1	0	1
OUTPUT	0	0	1	1	0	0	1	1

Table 8: Truth Table after applying firing rule in neural networks

The major differences between the above two tables gives the generalization of the neurons. This rule gives the neurons a sense of similarity, which makes them respond very sensibly for the patterns not seen during training. This property of firing rules helps the risk prediction component to identify unknown risks very accurately.

5.4. Implementation using Neural Networks and Back Propagation Algorithm

In this section, the use of Java to perform different operation is explained. The major advantage of using Java lies in its simplicity as an easy approach to design, write, compile and debug [75] [77]. This is also known as a platform-independent programming language that easy to learn. In our research, the proposed approach is obtaining the input values, converting the BP and blood sugar values in a vector matrix, training the hidden layers, initializing the weights randomly, applying the sigmoid function at needed locations, adding momentum values to generate output values from the vector matrix and sending the outputs to the checker [76]. The values must initially be retrieved from the database as the input for the RPC to assess the risk level for a patient. For retrieving these values, the following code was used, as shown in Listing 2.

```
ResultSet rs3=stmt.executeQuery("select * from slam
where pid="+ppid);
if(rs3.next()){
n1=rs3.getInt("oct");
n2=rs3.getInt("nov");
n3=rs3.getInt("dece");
n4=rs3.getInt("jan");
n5=rs3.getInt("feb");
n6=rs3.getInt("mar");
n7=rs3.getInt("apr");
n8=rs3.getInt("may");
n9=rs3.getInt("jun");
n10=rs3.getInt("jul");
System.out.printf("\n\nAfter Meal Expected:
%.2f",afterm)
after=result*afterm;
System.out.printf("\nAfter output neural :%.3f",after);
```

Listing 2: To retrieve the input values to the RPC

In the hidden layers, the random values are giving at the initial stages of neural networks. To give these random values the syntax **new MLPLayer[layersSize.length]** is used with random value **Random(1234)**.

```
Public  MLPSugur(int inputSize, int[] layersSize)
 {
  layers = new MLPLayer[layersSize.length];
  Random r = new Random(1234);
  for (int i = 0; i < layersSize.length; i++)
 {
   int inSize = i == 0 ? inputSize : layersSize[i - 1];
   layers[i] = new MLPLayer(inSize, layersSize[i], r);
  }
 }
```

Listing 3: To generate the random values of hidden layers

The input error values and hidden layer values need to be trained to identify the role of neural networks for the proposed approach. Input hidden layer weights are determined to calculate the activation values of hidden layer neurons, as shown in Listing 4. At the same time, to speed processing, the momentum values are applied to the hidden neurons, and are also applied in the proposed technique.

```
public float[] train(float[] error, float learningRate, float
momentum) {
   int offs = 0;
   float[] nextError = new float[input.length];
   for (int i = 0; i < output.length; i++) {
    float d = error[i];
    if (isSigmoid) {
     d *= output[i] * (1 - output[i]);
    }
    for (int j = 0; j < input.length; j++) {
     int idx = offs + j;
     nextError[j] += weights[idx] * d;
     float dw = input[j] * d * learningRate;
     weights[idx] += dweights[idx] * momentum + dw;
     dweights[idx] = dw;
    }
    offs += input.length;
   }
   return nextError;
  }
 }
```

Listing 4: To train the hidden layer values and weights with momentum levels

These trained values and weights need to be initialized randomly, and for that the following code is used, as shown in Listing 5. After activating all these functions, the sigmoid function is applied for comparison to perform the neural operation. The code for applying the sigmoid function is shown in Listing 6, in which a back propagation function is used.

```
public void initWeights(Random r) {
  for (int i = 0; i < weights.length; i++) {
   weights[i] = (r.nextFloat() - 0.5f) * 4f;
  }
 }
```

Listing 5: Initializing the weight values randomly

```
public float[] run(float[] in) {
  System.arraycopy(in, 0, input, 0, in.length);
  input[input.length - 1] = 1;
  int offs = 0;
  Arrays.fill(output, 0);
  for (int i = 0; i < output.length; i++) {
   for (int j = 0; j < input.length; j++) {
    output[i] += weights[offs + j] * input[j];
   }
   if (isSigmoid) {
    output[i] = (float) (1 / (1 + Math.exp(-output[i])));
   }
   offs += input.length;
  }
  return Arrays.copyOf(output, output.length);
 }
```

Listing 6: Applying the sigmoid function

Using the above Listings 4 to 7, our approach performs the neural operation to process the input values with the hidden layer values to identify the status of the patient's health condition. However, these values will be in matrix form, and to obtain these hidden layer values, the following code is used to generate output values.

```
int en = 100;
  for (int e = 0; e < en; e++) {

   for (int i = 0; i < res.length; i++) {
    int idx = r.nextInt(res.length);
    mlp.train(train[idx], res[idx], 0.3f, 0.6f);
   }

    if ((e + 1) % 100 == 0) {
    System.out.println();

 for (int i = 0; i < res.length; i++) {
    float[] t = train[i];

System.out.printf("%d epoch\n", e + 1);
    mres=(mlp.run(t)[0]);
    temp +=mres;
System.out.printf("%.1f,    %.1f    -->    %.3f\n",    t[0],
t[1],mres);
    }
            result=(nnout+errorvalue-hiddenweight);
```

Listing 7: To generate output values from the hidden layers

These values are needed to be compared with the ideal conditions, and hence the predicted values need to be available to the checker. The communication between RPC and checker is established using the following code, as shown in Listing 8.

```
try{
            pstmt   =con.prepareStatement("update   checker   set
beforem=?,afterm=? where sno=1");
            pstmt.setDouble(1,before);
            pstmt.setDouble(2,after);
        pstmt.executeUpdate();
System.out.println("\nFinal Output Send to the Checker...");
}
catch(Exception e2){e2.printStackTrace();
}
```

Listing 8: Sending the predicted value from RPC to checker

5.5. Runtime Monitoring

In the proposed approach, runtime monitoring examines the status of patient blood pressure levels and glucose levels. These levels were processed through neural networks, and the output of the neural network was available at the input of the checker. These values are tested against the ideal values in the database, as defined by the hospital team management. The checker checks the health status of patients to test whether patient blood glucose and BP levels are within or beyond the ideal range.

5.5.1. Checker

The checker aims to test various conditions of patient health conditions, and at runtime it retrieves the values from the RPC and database. This is a cycle of collecting updates and comparing them to different levels. The checker syntax is given in Listing 9.

```
If Parameter(1) True then
        Check(RiskType (1));
If Parameter (2) True then
        Check(RiskType (1));
.
.
.
.
If Parameter (n) True then
        Check(RiskType (n));
```

Listing 9: Checker Syntax

In the runtime, the checker continuously checks for updates from the RPC component. On receiving a new output from the RPC, the checker will attempt to retrieve information from the database for the relevant parameter. The code for retrieving values from the RPC to the checker is given in Listing 10.

```
rs=st.executeQuery("select * from checker where sno=1");
 if(rs.next()){
ppid=rs.getInt("pid");
beforem=rs.getDouble("beforem");
afterm=rs.getDouble("afterm");
highbp=rs.getDouble("highbp");
lowbp=rs.getDouble("lowbp");
}
```

Listing 10: To retrieve the values from RPC to checker input

5.5.2. Assertion Technique at runtime

Assertion is used to test the conditions made in a program. The main function of this assertion is to validate the program used by checking the exceptions and logical errors [79]. Assertions enable description of behaviour of class and method in a precise manner. These are the elements of system specifications and they explain the corrected condition towards different classes and methods. One can check parts of implementation at runtime, and the assertions can be checked while executing the programs [77] [78] [146].

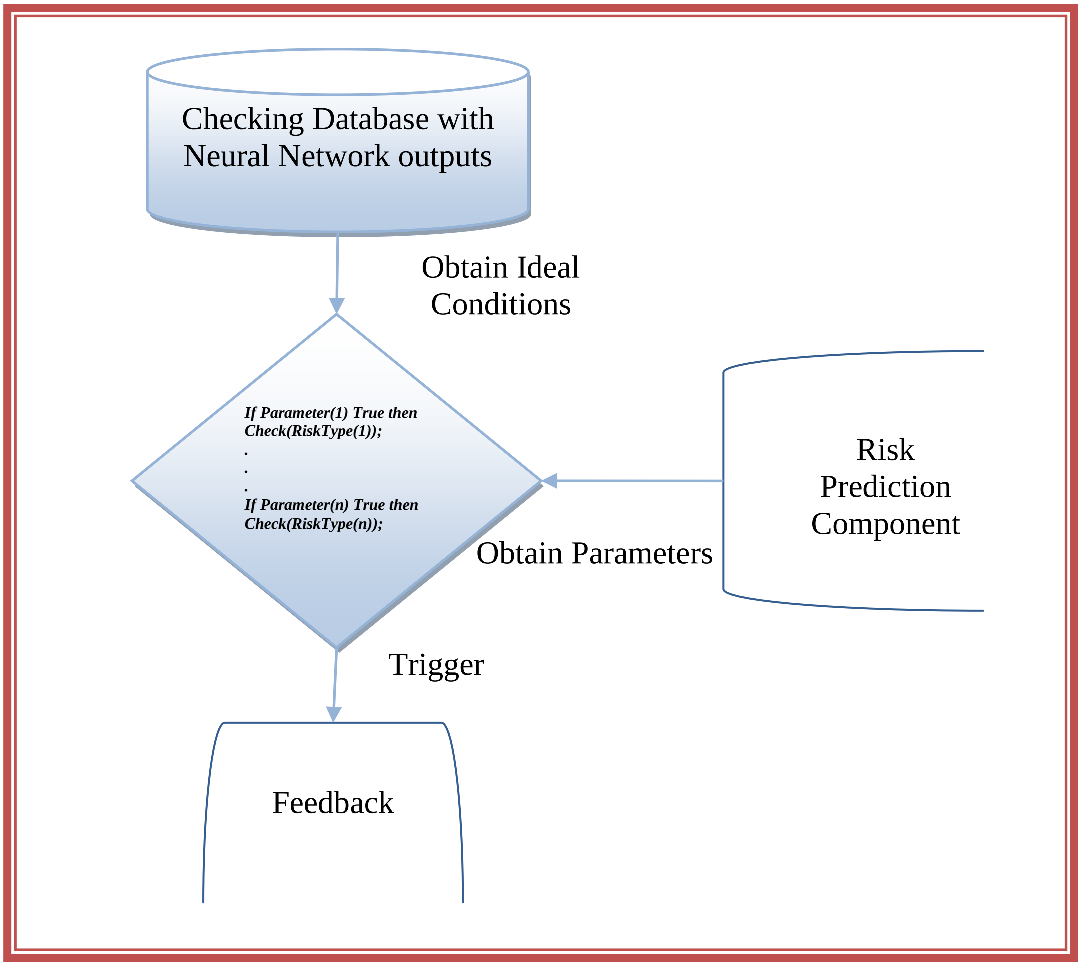


Figure 21: Checker process in runtime monitoring component

Generally, assertions guide the programmer to avoid the maximum number of errors, and there are two types: precondition and post condition. Precondition assertions are invoked during the process of invoking a method. Post condition assertions are invoked after a method is finished. Use of assertions in Java makes the process easier to understand and more user friendly as it can be implemented before or after defining the conditions of the program. Assertions can be used for control flow and internal and class invariants for improving the program experience [79].

```
if(beforem<60 || beforem>400)
{
Out.println("Unknown parameter for before meals");
}
if(beforem>=60 && beforem<82)
{
Out.println("Hypoglycaemia for before meals");
}
if(beforem>=82 && beforem<=110)
{
Out.println("NORMAL for before meals");
}
if(beforem>110 && beforem<=400)
{
Out.println("Hyperglycaemia  for before meals");
}
```

Listing 11: To check sugar levels at different defined levels as per medical standards

5.6. Summary

In this chapter, the functioning of risk prediction was explained using Java-based neural networks programming. The prediction method was defined and clearly explained using different Java functionalities. This chapter also considered different conditions of risk variables according to medical standards, and predicted risk levels for various diabetic patients in Saudi Arabian hospitals. The next chapter will concentrate on implementing the prototype for ERWS approach.

Chapter 6: System Prototype

Objectives

- To design the prototype for the early risk warning system approach
- To describe the implementation of prototype classes
- To support the research presented in this thesis

6.1. Introduction

This chapter designs the system prototype of the proposed approach. Section 6.2 explains the hospital environment and its functionalities. The advantages of an SQL trigger are explained in section 6.3, and its role in database and runtime monitoring is highlighted. The prototype for the proposed research is drawn and explained in section 6.4, and a class diagram explaining the proposed approach was drawn in section 6.5.

6.2. Hospital Environment: Patient Information

Our system architecture incorporates Java-based neural networks to assess the blood sugar and BP levels of a patient in a hospital environment. The use of Java in this implementation provides an easier method of application development to implement the desired functionalities of the research objectives. These objectives include an early warning for risks, which needs to be faster to process the parameters of a patient's BP and blood sugar levels. At the same time, the use of the MySQL server is preferred due to the simple nature of retrieving data from the database for various operations. The major advantage of using the MySQL server is to provide the entire corpus of information from different operations in one database [139] [140]. In this research, information was collected from 200 patients including various parameters like blood sugar levels after and before meals and high and low blood pressure levels. This database also stores the ideal conditions of various risk factors and normal parameters according to medical standards. Thus, our prototype deals with the overall information of 200 patients' inputs and relevant executed output parameters from various components of the architecture.

6.3. SQL Trigger Technique

This is an independent technique connected to the database with a table for performing predefined actions at specific times. In our proposed approach, the trigger is used to alert the patient and hospital management team when an unknown parameter is identified or to provide feedback about no risk/known risk. This technique observes the tables to collect new information about different parameters and updates the database with new records for patients. The SQL trigger syntax contains three parts: condition, rules and actions [147]. The SQL trigger structure for this is given in Listing 12.

```
CREATE [or REPLACE ]
TRIGGER trigger - name
BEFORE [ or AFTER ]
INSERT [or UPDATE ]
ON table - name
FOR EACH ROW
BEGIN
IF condition 1 THEN
ACTION 1
IF condition 2 THEN
ACTION 2
.
.
.
IF condition n THEN
ACTION n
END ;
```

Listing 12: Structure of SQL Trigger

The reasons for using the SQL Trigger in the prototype of ERWS architecture is explained as follows:

- The information of all activities from different components is stored in the database using this trigger. Use of such a method will be an easy and efficient approach to collect necessary information from the database in the hospital environment.
- The source code of the total architecture will not be affected by using the SQL trigger since the ERWS approach establishes communication with only the database.
- The use of Java and its simple nature of programming were used to develop the prototype of current architecture. Additionally, using the SQL trigger makes this process simpler as the triggers are directly connected to the database.

6.4. Prototype Structure

An early risk warning system proposed in our architecture is structured into eight (8) key components as shown in Figure 23. The objective of the proposed early risk warning system is based on predicting risk parameters and unknown parameters while the system is running. Prototype components of ERWS as shown in Figure 23 were explained in Chapter 4 in detail. In this prototype, the database must connect directly with the SQL Trigger to establish direct communication. All other components work and communicate with each other to achieve the objectives of the proposed research.

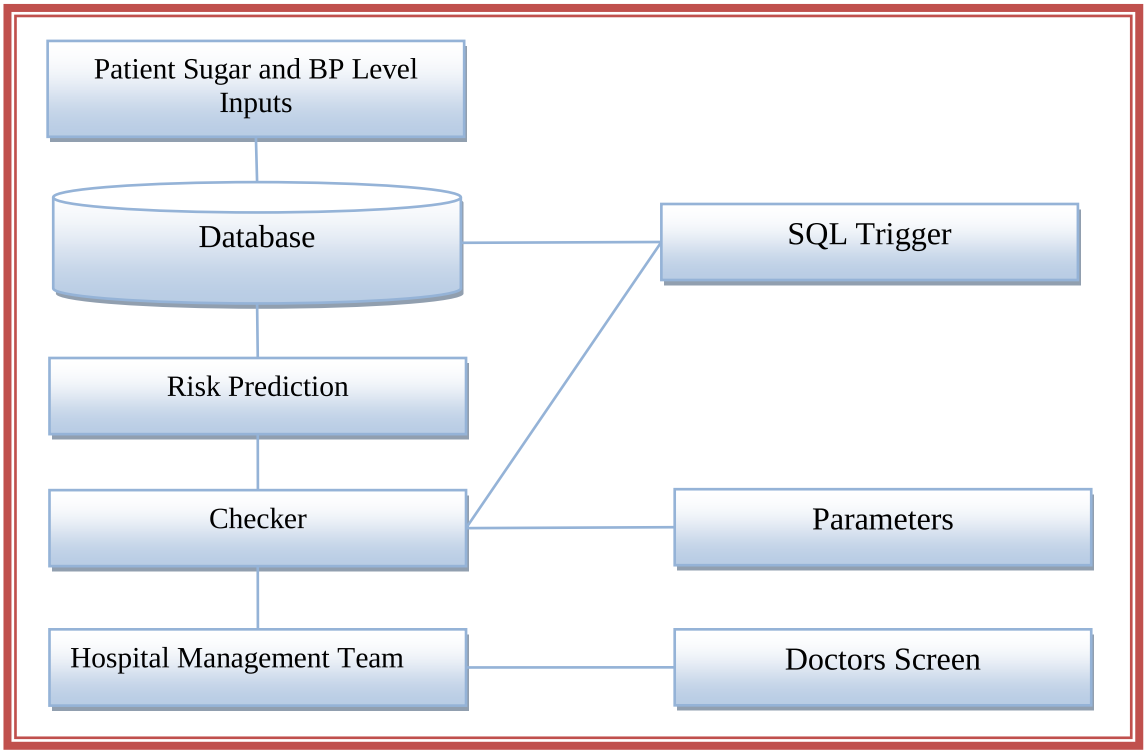


Figure 22: Structure of proposed prototype

Table 9 explains the classes defined in the prototype with various system components and the interlinking relation in the proposed architecture as shown in Figure 12.

Class	Related Components
Patient blood sugar and BP Levels	Hospital Environment and Risk Prediction
SQL Trigger	Runtime Monitoring
Database	Runtime Monitoring
Checker	Runtime Monitoring
Feedback	Runtime Monitoring

Table 9: Components of Prototype Vs Components of Architecture

6.5. Prototype Class Diagram

The class diagram shown in Figure 23 explains the attributes and operations of each component in which the attributes explain properties of different classes and the operations explain the methods of the class that is going to perform some action. The class diagram here explains the relationships between all classes of the prototypes. The description of these classes including their method is located in Appendix A.

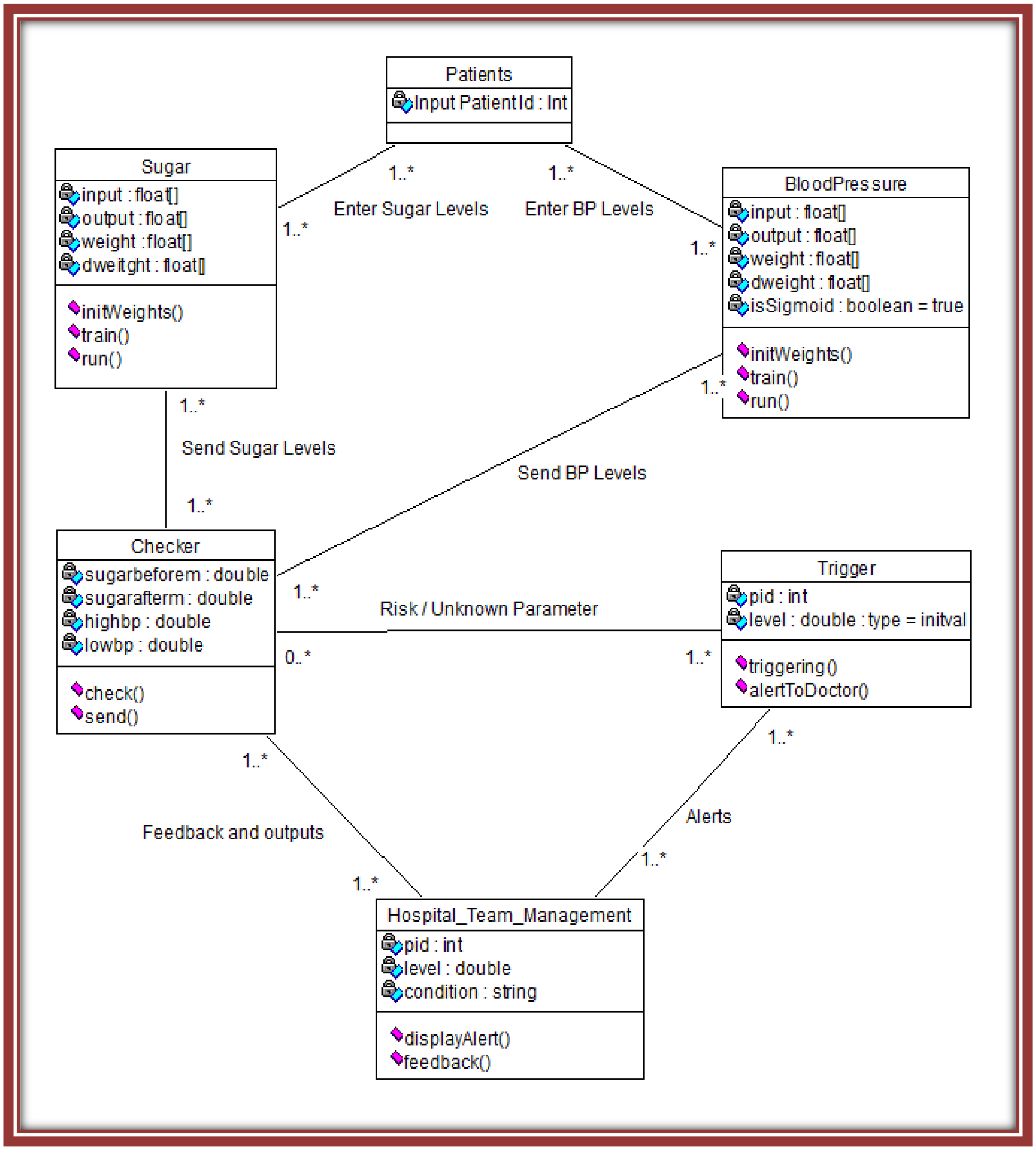


Figure 23: ERWS Prototype Class Diagram

6.6. Summary

The high-level design of prototype implementation for the proposed approach was given in this chapter. It provided an overview of the proposed prototype by considering the hospital environment for which the system was developed. The use of the SQL trigger was highlighted and the interaction between the SQL trigger and database was highlighted with appropriate justification for selecting it in the proposed research. The components and attributes of this architecture are explained with their operations. A class diagram representing the relationships and mapping the system architecture is shown in detail. The next chapter will discuss the result and evaluations of the EWRS approach with observations.

Chapter 7: Evaluation

Objectives

- To evaluate the implementation of the early risk warning system approach
- To present the results of executing system components
- To evaluate the use of neural networks with runtime monitoring

7.1. Introduction

In this chapter, a case study is discussed with different scenarios of patient health conditions according to medical standards. Section 7.2 focuses the case study with the analysis of a patient's information using a back propagation algorithm to find the hidden layer values. The risk levels identified for different patients with known parameters according to medical standards are evaluated in section 7.3. The predictions of unknown parameters are explained in section 7.4. A detailed discussion of the outcomes of the results and highlights of different achievements is made in section 7.4.

7.2. Case Study

In this case study, the hospital environment checks the blood sugar and BP levels of a patient, providing these levels for RPC to test the health status of a patient, which is changing continuously. Only the within-hospital environment is considered here, though in real-time the facility of checking blood glucose levels using Continuous Glucose Monitors (CGM) is available [86]. Patients use these CGM devices generally when they are roaming outside the hospital environment. However, to test the proposed approach, the information collected is from the hospital environment only. In this case study, two scenarios are discussed. The first scenario explains the identification of risks/normal health conditions as defined by medical standards, and the second explains the identification of unknown parameters, which are not available in medical standards.

This section evaluates the approach of ERWS using a number of scenarios to explain the implementation of ERWS with the results obtained from the execution of components.

7.2.1. Defining the Standard Conditions of Patient Glucose and BP Levels and Risks

Blood sugar levels in a human body will change as per the diet levels. These levels will increase after meals in a healthy patient. Therefore, blood sugar levels must be calculated before and after meals separately for a diabetic patient. Normal human glucose levels are given in Table 10. Similarly, the blood pressure levels of a human body will change according to the health status of a patient. BP levels are measured as high BP and low BP. These values for ideal conditions in different scenarios are given in Table 10 [80 – 87].

Risk Type	**Inputs**	**In mg/dL**
Blood Sugar Levels		
Normal Patient	Before Meals	82 to 110
	After Meals	82 to 140
Low Blood Sugar Levels (**Hypoglycaemia**)	Before Meals	50 to 81
	After Meals	60 to 81
Unknown Parameter	Before Meals	<50 & >81
	After Meals	<60 & >81
High Blood Sugar Levels (**Hyperglycaemia**)	Before Meals	111 to 300
	After Meals	141 to 400

Unknown Parameter	Before Meals	<111 & >300
	After Meals	<141 & >400
Blood Pressure Levels	**In mm/Hg**	
Normal Patient	82 to 110	
Low Blood Pressure Levels (**Hypotension**)	50 to 81	
Unknown Parameter	< 35 and >130	
High Blood Pressure Levels (**Hypertension**)	111 to 300	
Unknown Parameter	< 50 and > 240	

Table 10: The standard levels of blood sugar and BP according to medical standards

The sample outputs of five patients are shown in Table 11 along with health condition and status. In the next sections, four scenarios will be discussed based on the risk types, and a detailed analysis will be given.

7.2.2. Response of Neural Networks using Back Propagation Algorithm on Prediction

The back propagation algorithm plays a key role to in defining the hidden layers and their weight during the process of communicating between hidden layer values and input values. The floating values between 0 and 1 generated at the input layers of the neural networks will be compared with the hidden layer values generated by training those values. A set of trained values for the patient with ID 121 is shown in Figure 24, along with the calculations of input hidden neurons and output hidden neurons.

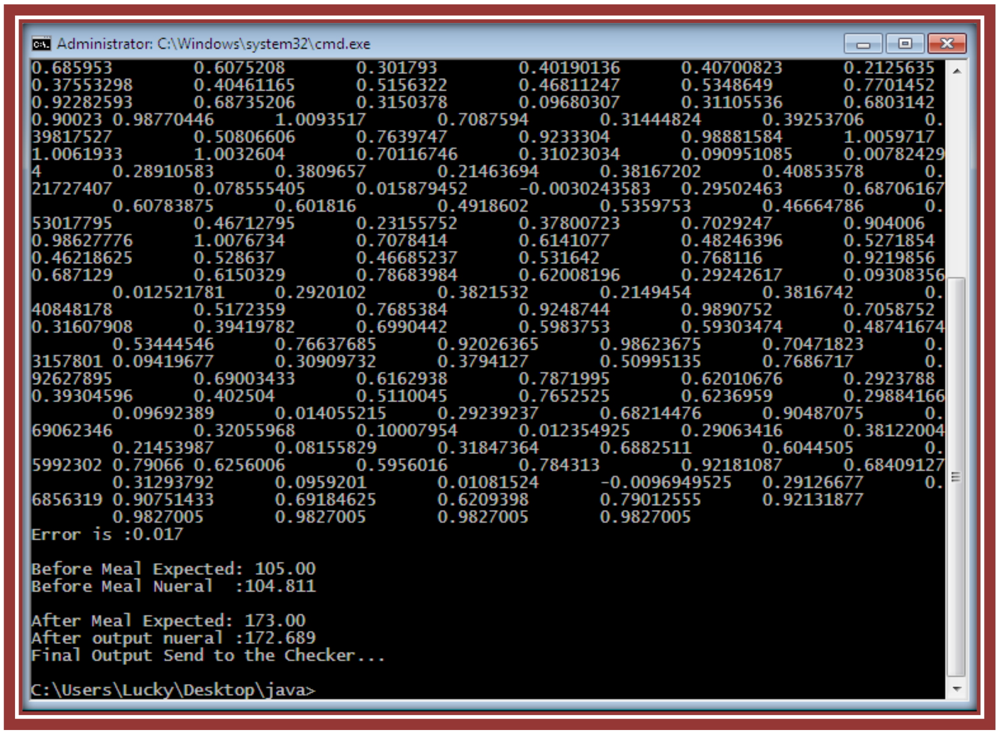


Figure 24: The values trained for hidden layers for patient 121

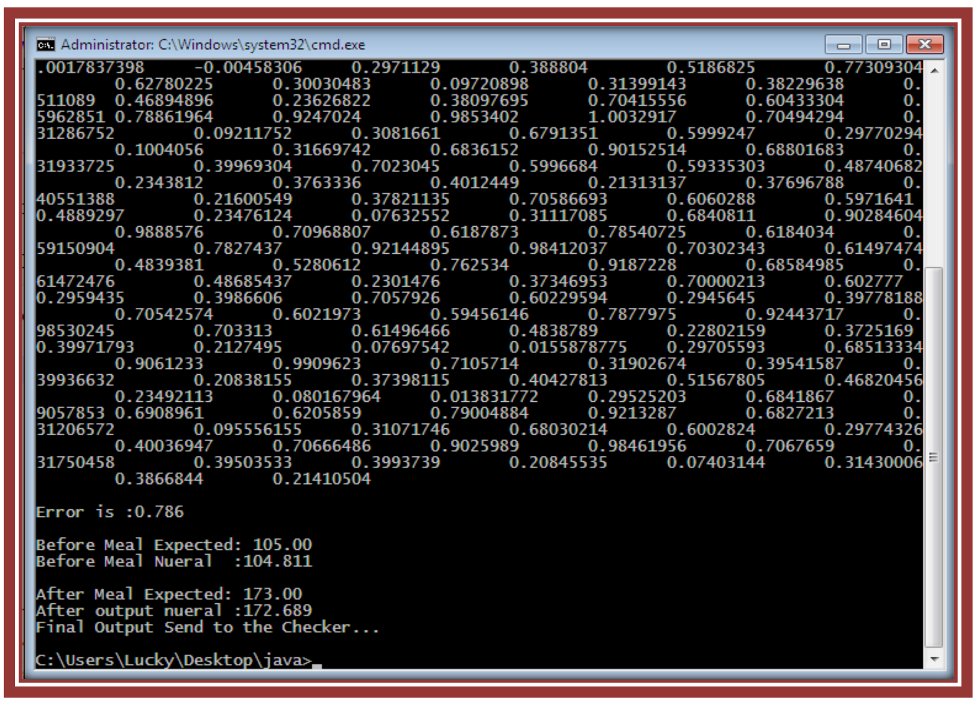


Figure 25: The output values at hidden layers for patient 121

First Input layer: The weight values for weight matrix 1 are considered and relevant calculations shown below:
0.0017837398, -0.00458306, 0.2971129, 0.388804, 0.5186825, 0.77309304

Input of hidden neuron 1: (0 * 0.0017837398) + (1 * 0.2971129) = 0.297113

Input of hidden neuron 2: (0 * -0.00458306) + (1 *0.388804) = 0.388804

Output of hidden neuron 1: 1 / (1 + exp (-0.297113)) = 0.573737

Output of hidden neuron 2: 1 / (1 + exp (-0.0.388804)) = 0.509719

<u>The neurons in the output layer are activated at momentum rate 0.05f:</u>

Input of output neuron: (0. 573737* 0.05) + (0. 509719* 0.05) = 0.054173

Output of output neuron: 1 / (1 + exp (-0. 054173)) = 0.51354

Error value can be calculated by subtracting output from target: 0 - 0. 51354= -0.51354

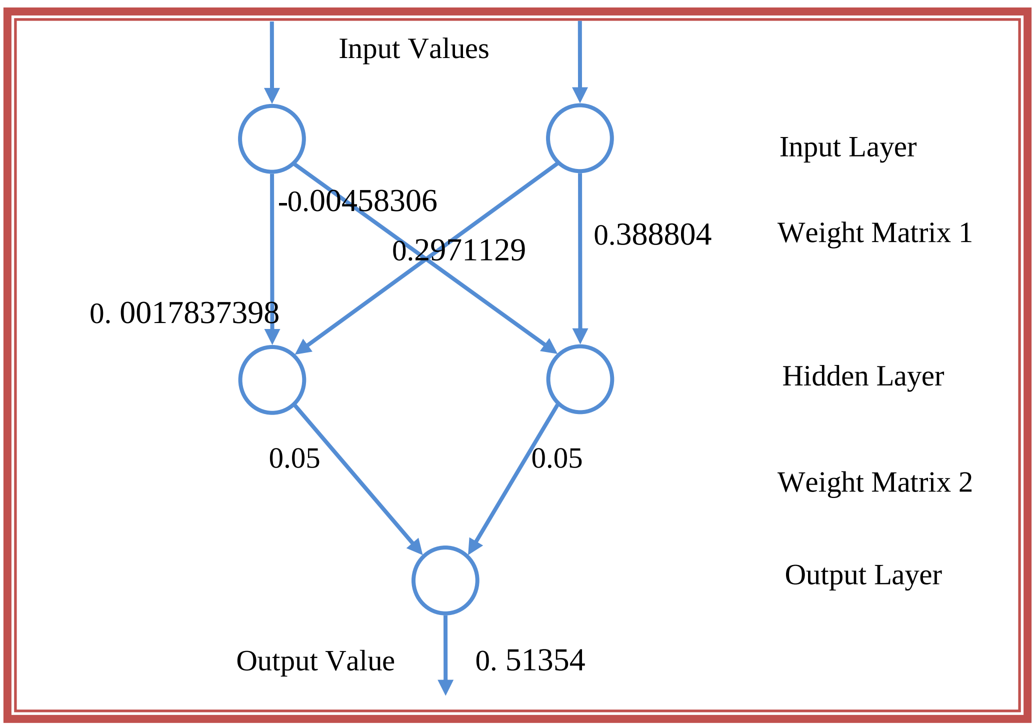


Figure 26: Calculated values for first hidden layer

In the above Figure 26, the output layer values and their calculations are shown along with the error value calculations. However, according to neural network theories, the speed of neural networks will improve by increasing the momentum values. For example, if the momentum value is increased to 0.5f from 0.05f, the output values in the output layer will show an increased value from 0.51354 to 0.625636. However, the result also shows that the possibility of increase in the error values is greater when the momentum value is increased.

The neurons in the output layer are activated at momentum rate 0.5f:

Input of output neuron: (0. 573737* 0.5) + (0. 509719* 0.5) = 0.51354

Output of output neuron: 1 / (1 + exp (-0. 51354)) = 0.625636

Error value can be calculated by subtracting output from target: 0 - 0.625636= -0. 62563

At runtime, the input variables tend to change regularly. In such situations, it is better to have higher momentum, as this increases the processing speed of the risk prediction component. Even when the error value is increased by a rise in momentum, the output values using neural networks give consistent results.

7.3. Risk Parameters Analysis of Blood Sugar and BP Levels of a Patient: Scenario 1

A rise in glucose levels can harm a diabetic person to the point of coma and serious illness. The blood sugar levels of a patient with hyperglycaemia must be in a range of 111 to 300 mg/dL before meals and 141 to 400 mg/dL after meals [87 – 88]. Similarly, patients with hypoglycaemia have sugar levels as shown in Table 10. BP levels are also mentioned in this table, along with the risk types (hyperglycaemia, hypoglycaemia, hypertension and hypotension) according to medical standards. These conditions are tested for the patient with ID 292. Testing steps for checking the proposed approach are as follows:

Step – 1: Testing Patient Health Status

To check different patients' conditions, enter the patient ID and the corresponding health status details of the patient will be displayed. The basic screen for testing the health status of a patient is shown in Figure 27. This screen shows the hospital environment where patient information can be seen individually and overall patient health status also can be displayed.

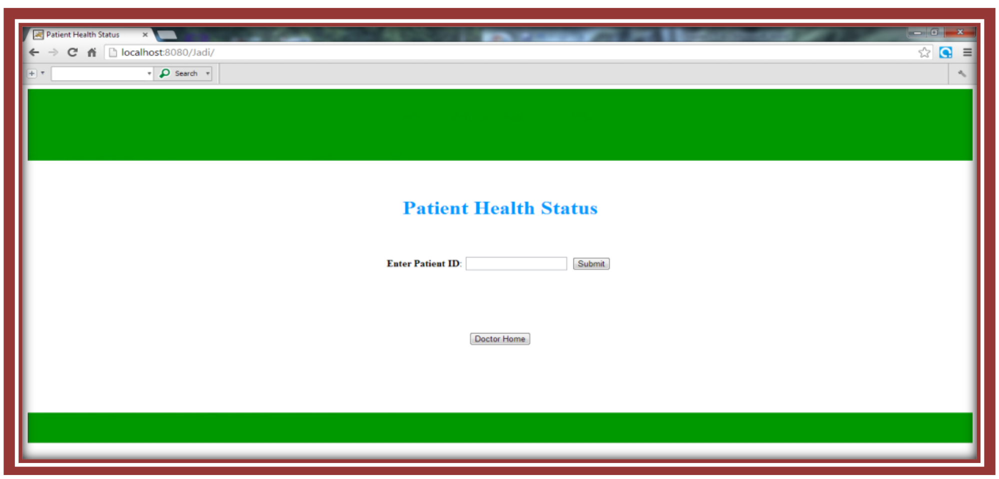


Figure 27: The basic screen for testing the health status of patients

Step 2: Checking the Health Status of Patients

Enter the patient ID and observe the screen for the patient's current health condition. Before getting the final outputs, the risk prediction component will be processed using neural networks. This process can be seen in Figure 28. The patient ID 292 was entered and the risk prediction component delivered the outputs as shown in Figure 29.

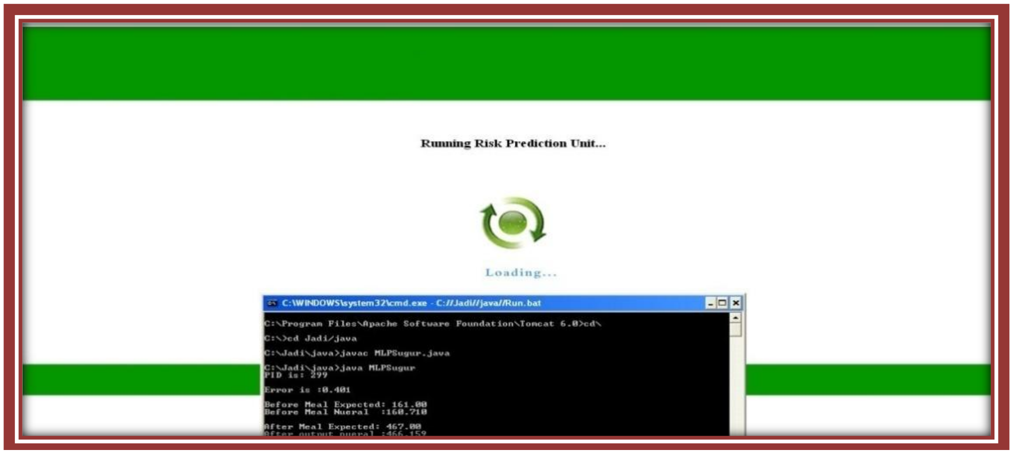


Figure 28: Processing of risk prediction component at runtime

The risks identified for all four parameters are displayed in Figure 29 with corresponding risk types as per medical standards. The recommendations are a part of the mitigation process in the proposed approach, and they have been recommended according to medical standards.

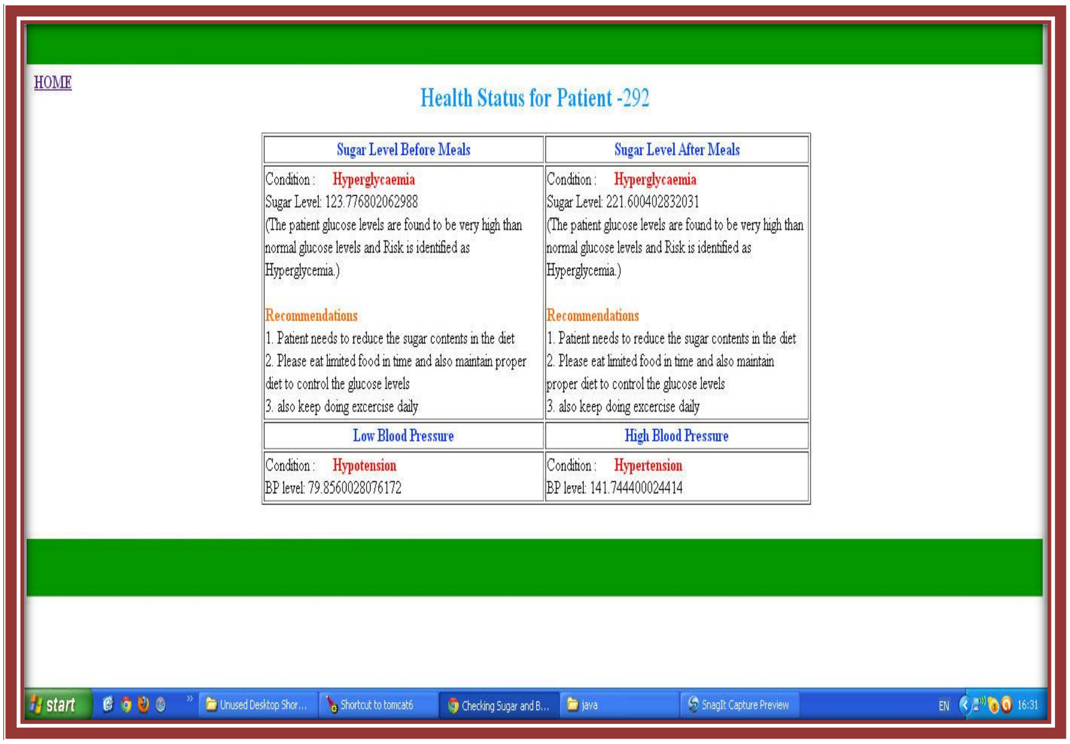


Figure 29: Outputs of patient 292 delivered using the proposed ERWS approach

The above three figures (shown in 27, 28 and 29) are only screen shots while the system is processing. However, internally many actions take place using the proposed approach as explained in Chapters 3, 4 and 5. Different layers of NN in RPC for different input parameters (i.e. blood sugar levels before and after meals and high and low BP levels in this research) as shown in Figure 13 are processed simultaneously. These layers give different output parameters based on the defined input values at the input of the RPC. Figure 30 explains the processing outputs of different parameters based on the corresponding inputs applied at RPC.

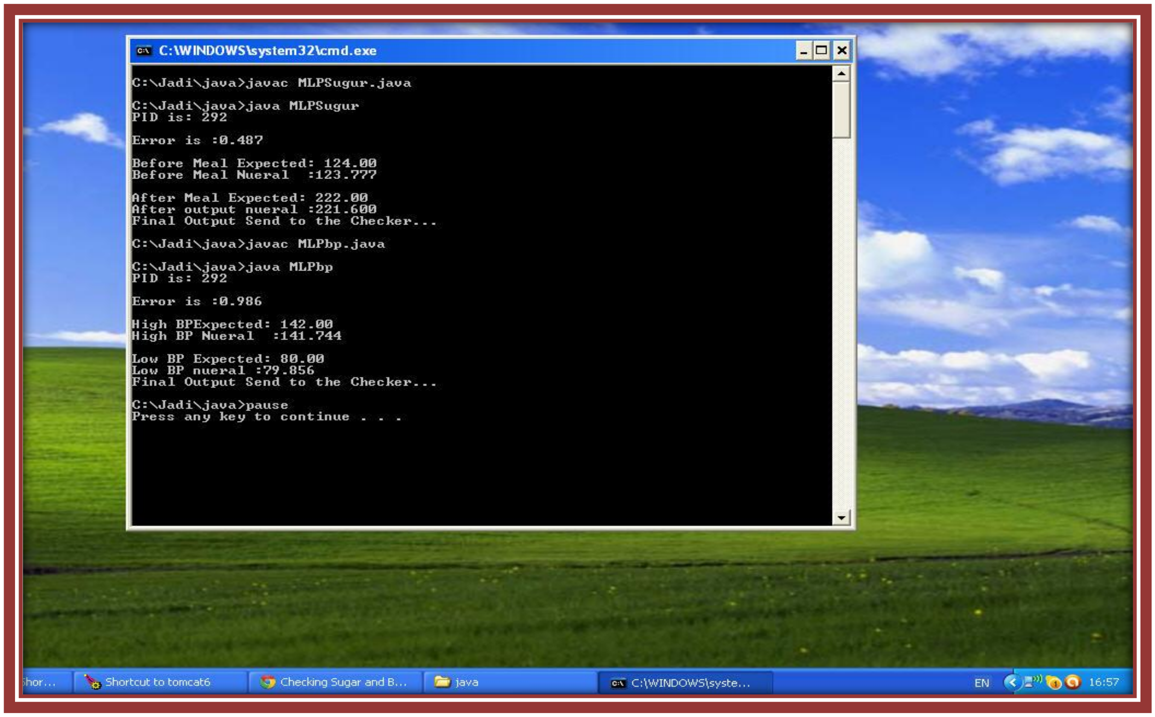


Figure 30: Overall outputs for different input parameters for patient 292

All four parameters are processed using neural networks for sugar and BP values of the patient, and they are displayed on one screen. However, all the NN layers have different formats of weight values and training values in the hidden layers of an RPC.

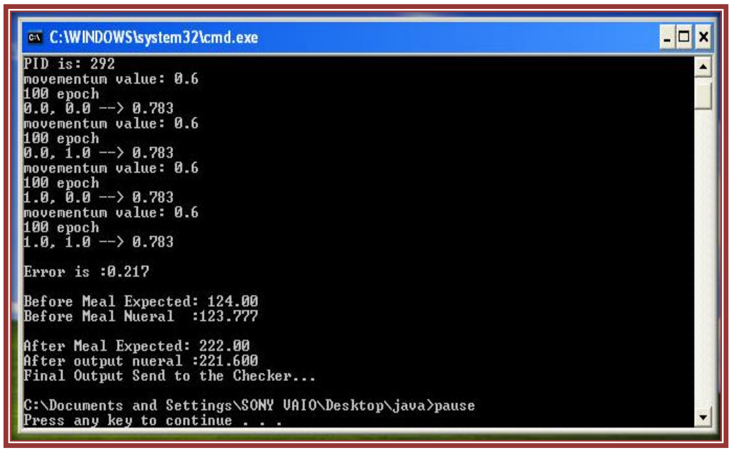


Figure 31: Momentum values applied at the NN layer

These hidden layer training and weight values, along with applied momentum are given in Figures 31, 32 and 33. These values are generated using the back propagation algorithm in the proposed approach. The momentum values applied to the hidden layers is shown in Figure 31 to increase the processing speed of the NN as explained in Chapter 5. This approach tested 10 input values for four parameters (blood sugar levels before and after meals and BP high and low values) of a patient (from the hospital), but in runtime, the input parameters for each patient are increasing. In such situations, the momentum value can be increased further to increase the processing speed of NN.

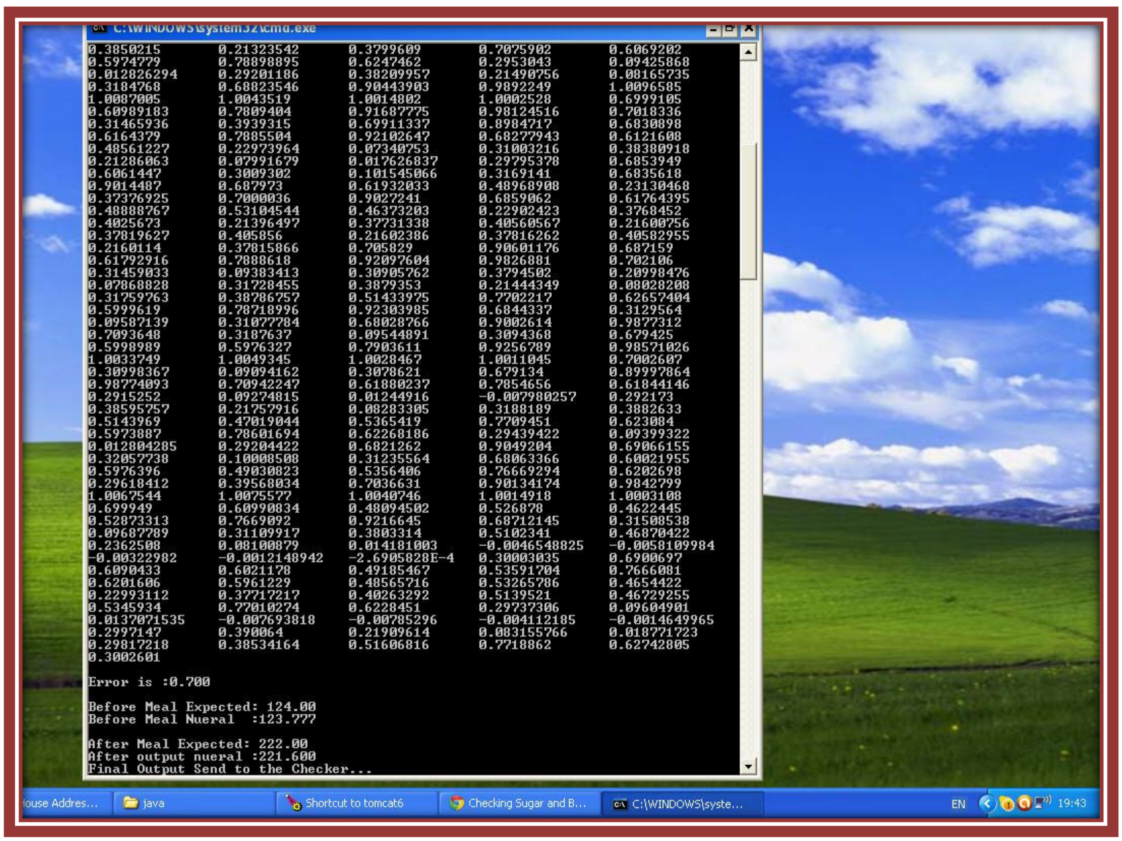


Figure 32: Trained values of the NN layer for blood sugar levels of patient 292

The training values and weight values of hidden layers shown in Figures 32 and 33 are based on the values that are generated by the back propagation algorithm. The analysis and calculations of these training values and hidden layer weight values are shown in section 7.2.2 for the patient ID 121.

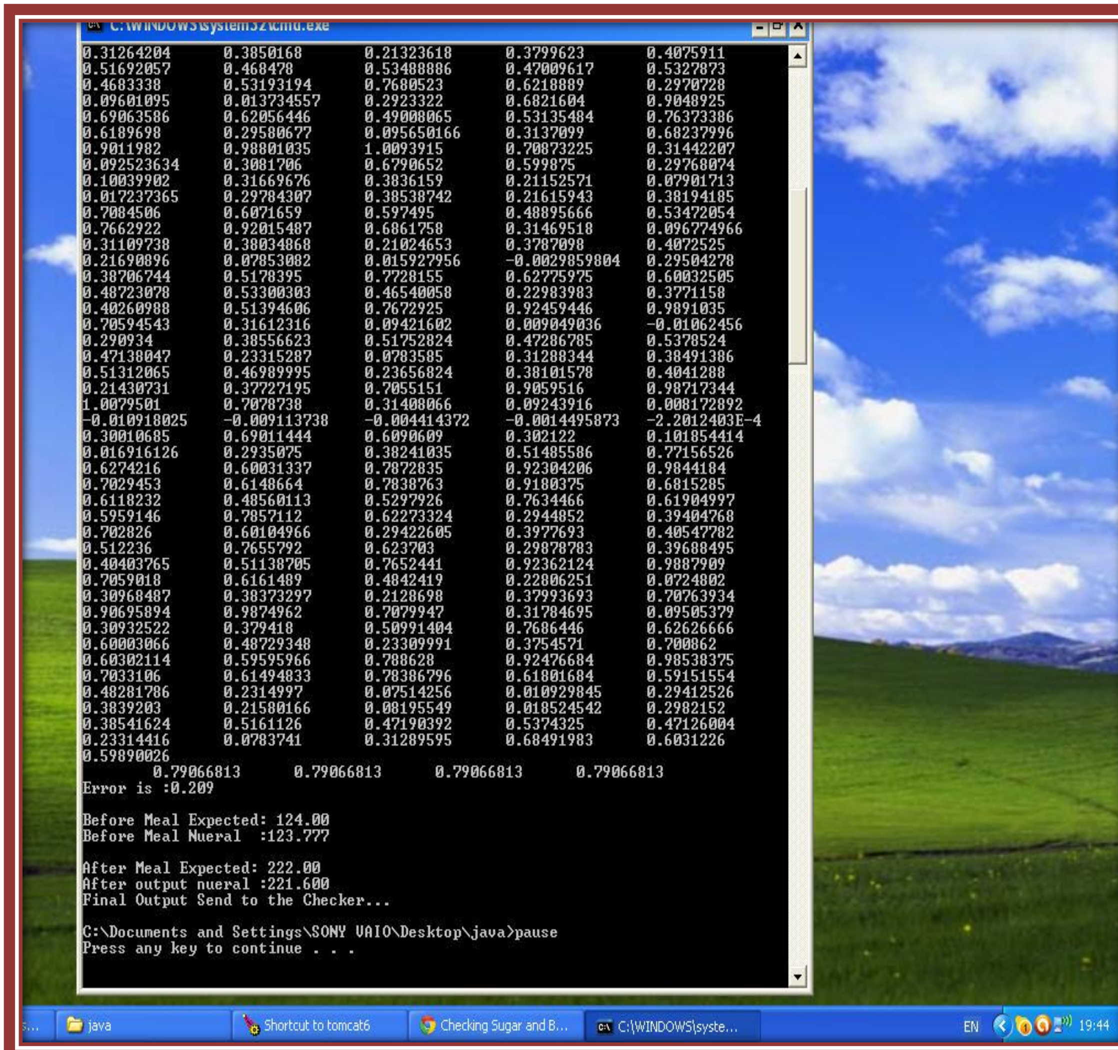


Figure 33: Weight values of NN layer for blood sugar levels of patient 292

7.4. Unknown Parameters Analysis of Blood Sugar and BP Levels of a Patient: Scenario 2

Lists of unknown values for different parameters are defined in Table 10, which are not defined in the reports of medical standards. The screen will be displayed with the status of an unknown parameter if the predicted value of a patient health condition is found in those ranges. For all four parameters tested in this proposed approach, the unknown parameter ranges are defined (see Figure 37).

- **Runtime Monitoring**

The proposed approach discussed two scenarios about proposed architecture and performance in runtime. Identification of the health status of a patient is the prime objective of the proposed approach, in which the checker operation will be a continuous process. The communications between all components are linked with the database by updating all inputs and outputs from different components (as explained in Chapter 6). The use of Java works as a communication interface between the database and risk prediction component in our proposed approach. The checker ensures that all conditions defined in the database as per medical standards are tested successfully (see Figure 34) as described in Chapter 5.

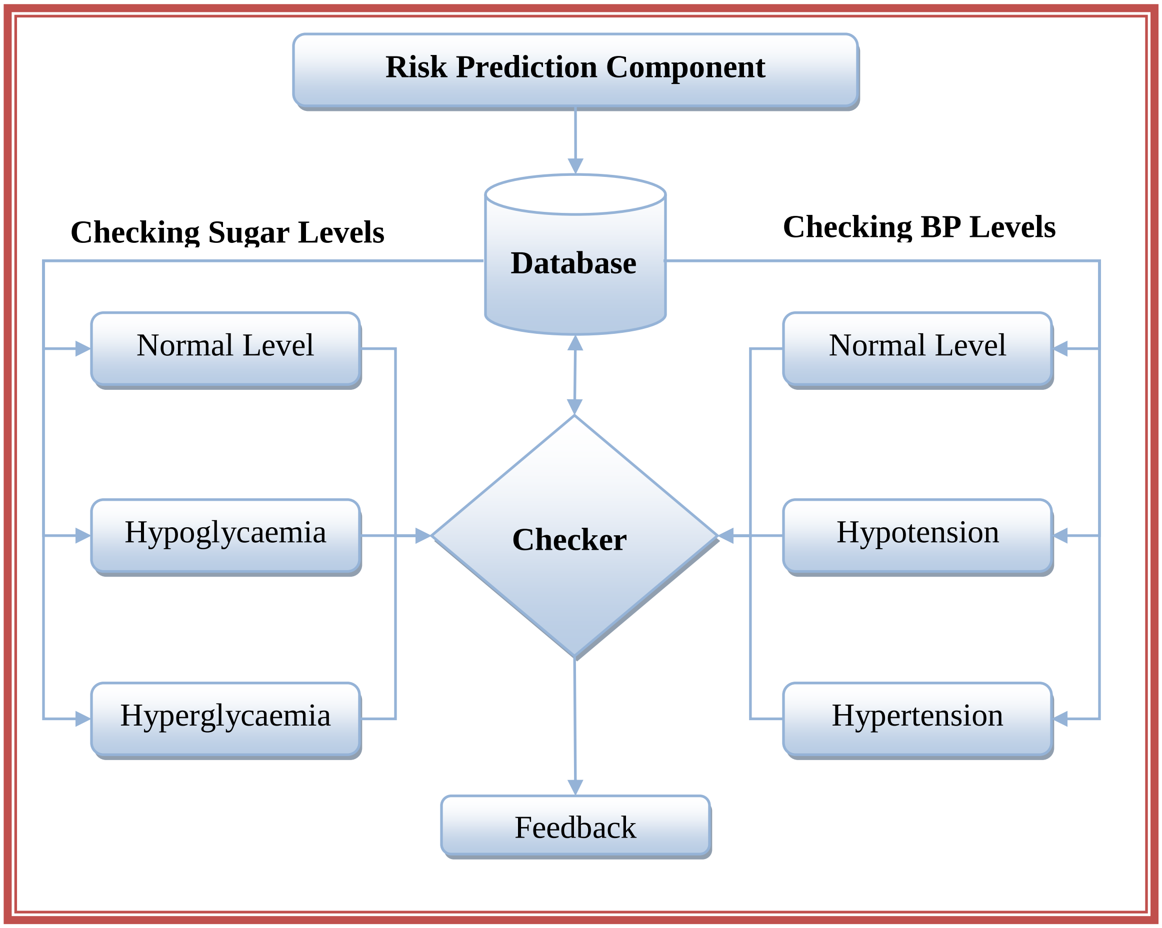


Figure 34: Checker activities in the proposed architecture

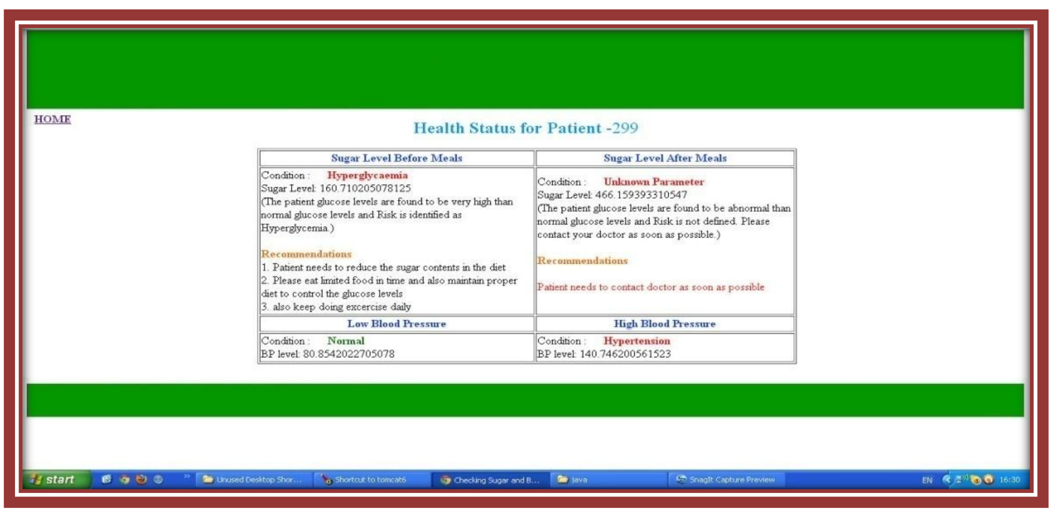


Figure 35: Unknown parameter identified for patient ID 299

During implementation, our approach identified one unknown parameter for patient ID 299 as shown in Figure 35 (see also 11). Health statuses with unknown parameter conditions are highlighted at the doctor's place. The trigger operation then takes place and alerts the doctors. The trigger operations are updated on the doctor's screen and database every five (5) seconds.

Figure 36: Trigger output for unknown parameter

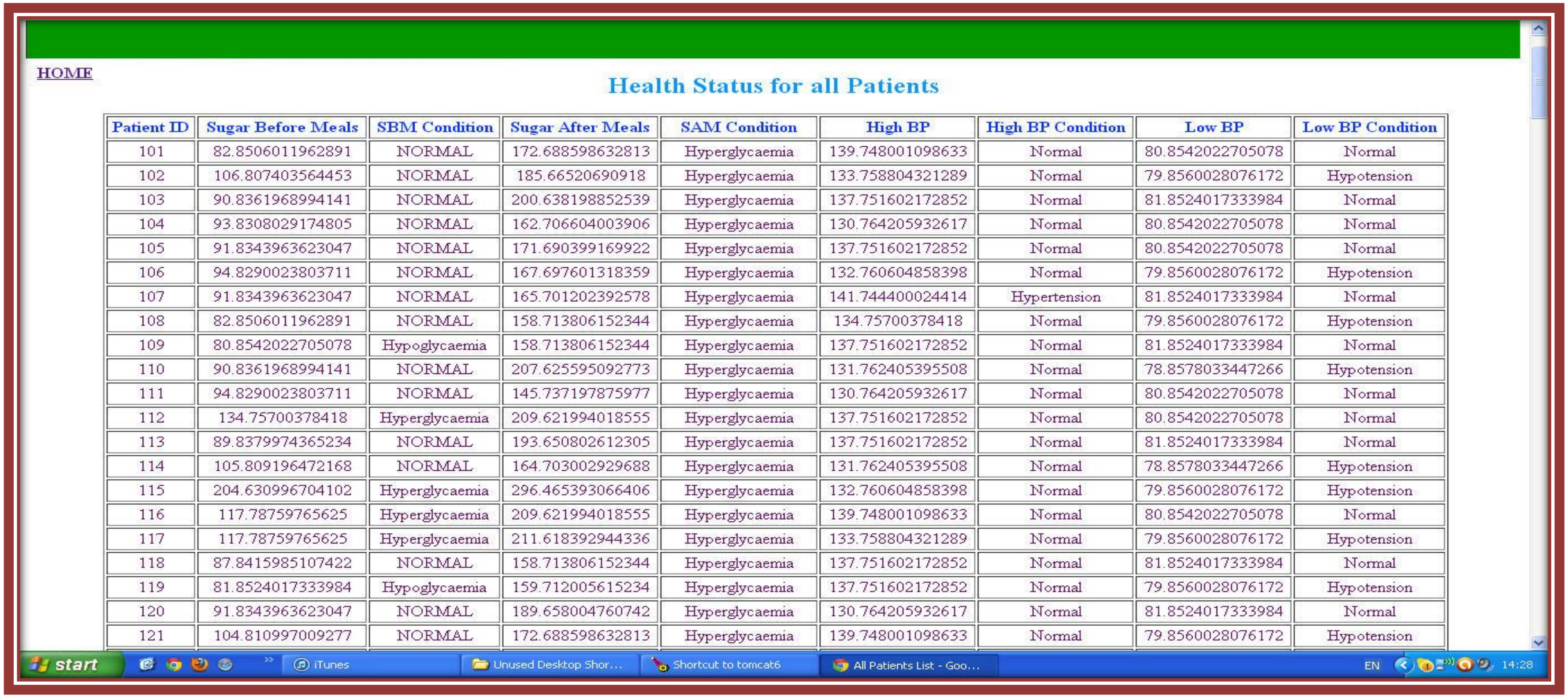
- **Trigger**

The trigger operation is activated whenever the checker component identifies an unknown parameter during the checking process (see the trigger syntax in Listing 13). This will generate an alert on the database and doctor's screen to communicate to the patient some good solutions at a high priority. The trigger operation is performed along with the checker operation to identify abnormal changes in patient health condition. The outputs from this process are updated with the database and hospital management team for five seconds (seen in Figure 36).

```
try{
Statement st2=con.createStatement();
st.executeUpdate("insert into doctor(pid,level) values('"+ppid+"','"+afterm+"')");
}catch(Exception e2){}
}
```

Listing 13: Trigger Syntax

Health status for overall patients will be displayed as shown in Figure 37 and for total 200 patients results see Appendix D.



HOME

Health Status for all Patients

Patient ID	Sugar Before Meals	SBM Condition	Sugar After Meals	SAM Condition	High BP	High BP Condition	Low BP	Low BP Condition
101	82.8506011962891	NORMAL	172.688598632813	Hyperglycaemia	139.748001098633	Normal	80.8542022705078	Normal
102	106.807403564453	NORMAL	185.66520690918	Hyperglycaemia	133.758804321289	Normal	79.8560028076172	Hypotension
103	90.8361968994141	NORMAL	200.638198852539	Hyperglycaemia	137.751602172852	Normal	81.8524017333984	Normal
104	93.8308029174805	NORMAL	162.706604003906	Hyperglycaemia	130.764205932617	Normal	80.8542022705078	Normal
105	91.8343963623047	NORMAL	171.690399169922	Hyperglycaemia	137.751602172852	Normal	80.8542022705078	Normal
106	94.8290023803711	NORMAL	167.697601318359	Hyperglycaemia	132.760604858398	Normal	79.8560028076172	Hypotension
107	91.8343963623047	NORMAL	165.701202392578	Hyperglycaemia	141.744400024414	Hypertension	81.8524017333984	Normal
108	82.8506011962891	NORMAL	158.713806152344	Hyperglycaemia	134.75700378418	Normal	79.8560028076172	Hypotension
109	80.8542022705078	Hypoglycaemia	158.713806152344	Hyperglycaemia	137.751602172852	Normal	81.8524017333984	Normal
110	90.8361968994141	NORMAL	207.625595092773	Hyperglycaemia	131.762405395508	Normal	78.8578033447266	Hypotension
111	94.8290023803711	NORMAL	145.737197875977	Hyperglycaemia	130.764205932617	Normal	80.8542022705078	Normal
112	134.75700378418	Hyperglycaemia	209.621994018555	Hyperglycaemia	137.751602172852	Normal	80.8542022705078	Normal
113	89.8379974365234	NORMAL	193.650802612305	Hyperglycaemia	137.751602172852	Normal	81.8524017333984	Normal
114	105.809196472168	NORMAL	164.703002929688	Hyperglycaemia	131.762405395508	Normal	78.8578033447266	Hypotension
115	204.630996704102	Hyperglycaemia	296.465393066406	Hyperglycaemia	132.760604858398	Normal	79.8560028076172	Hypotension
116	117.78759765625	Hyperglycaemia	209.621994018555	Hyperglycaemia	139.748001098633	Normal	80.8542022705078	Normal
117	117.78759765625	Hyperglycaemia	211.618392944336	Hyperglycaemia	133.758804321289	Normal	79.8560028076172	Hypotension
118	87.8415985107422	NORMAL	158.713806152344	Hyperglycaemia	137.751602172852	Normal	81.8524017333984	Normal
119	81.8524017333984	Hypoglycaemia	159.712005615234	Hyperglycaemia	137.751602172852	Normal	79.8560028076172	Hypotension
120	91.8343963623047	NORMAL	189.658004760742	Hyperglycaemia	130.764205932617	Normal	81.8524017333984	Normal
121	104.810997009277	NORMAL	172.688598632813	Hyperglycaemia	139.748001098633	Normal	79.8560028076172	Hypotension

Figure 37: The outputs of health status of all patients

Patient ID	Sugar Before Meals	SBM Condition	Sugar After Meals	SBM Condition	High BP	High BP Condition	Low BP	Low BP Condition
102	106.807403564453	NORMAL	185.66520690918	Hyperglycaemia	133.758804321289	Normal	79.8560028076172	Hypotension
114	105.809196472168	NORMAL	164.703002929688	Hyperglycaemia	131.762405395508	Normal	78.8578033447266	Hypotension
182	81.8524017333984	Hyperglycaemia	202.63459777832	Hyperglycaemia	142.742599487305	Hypertension	79.8560028076172	Hypotension
292	123.776802062988	Hyperglycaemia	221.600402832031	Hyperglycaemia	141.744400024414	Hypertension	79.8560028076172	Hypotension
299	160.710205078125	Hyperglycaemia	466.159393310547	Unknown Parameter	140.746200561523	Hypertension	80.8542022705078	Normal

Table 11: The neural networks outputs of blood sugar and BP levels

7.4 Discussion

The research proposed an approach for an early warning system for risk management with the aim of providing feedback and alerts for both patients and hospital management teams with the updates of predicted parameters. This system will help both doctors and patients to take the appropriate precautionary steps to mitigate parameters. This research show how risks can be predicted in advance, while the system is running. The idea proposed in this research deals with real values collected from a hospital in Saudi Arabia, given appropriate evaluation for patient health conditions. The following are the added advantages of our proposed approach:

- The proposed ERWS approach is capable of monitoring the patient in all kinds of environments without any support from doctors. However, in a traditional healthcare setting, the values of blood sugar and BP levels must be monitored by someone periodically.
- This approach of ERWS is capable of alerting the database and hospital management team automatically when an unknown parameter is identified. However, in traditional healthcare methods, one of the team members needs to be actively monitoring the patient’s health condition.
- The ERWS can predict risk parameters by assessing patient health conditions continuously. The entire corpus of patient data with respect to time will be available for doctors and hospital management teams to mitigate the problems carefully with information about temporal changes. However, in traditional methods, patient records are maintained on an hourly basis or a few times a day.

Traditional healthcare methods (as discussed in Chapter 2) are using various best practices to monitor patients in an effective manner. However, most of these methods are found to be static, and the involvement of experts/doctors in observing the conditions is always necessary. The proposed approach avoids most human errors and helps to reduce risk prediction time. It works as an interface between the patient and hospital management team to reduce the effort of risk prediction and continuous monitoring.

The use of neural networks in the risk prediction component makes the prediction process more precise (as discussed in Chapter 2). Processing and Assessing a large number of values in traditional computing methods sets the stage for a large number of errors and requires extra effort to obtain an accurate value while operating the system in runtime. However, the proposed risk prediction component is capable of handling large numbers of input values and parameters at a time (as described in Chapter 5). With the purpose of avoiding the problems related to software programming, SQL triggering is directly connected to the database. Due to which other system components will function properly even if another component fails. This in turn reduces the risk of overall damage to hospital functionalities and patients.

The proposed approach was tested on 200 patients (detailed in Appendices C and D) and the outcomes are delivered to the nearest approximate values every time, the matched to defined ranges according to medical standards. Use of neural networks in this works like a human brain in the absence of doctor support [101].

7.5. Summary

ERWS evaluation was carried out in this chapter. A case study was presented to show how the back propagation using neural networks predicts risk levels. The risk levels defined in the scenario were based on the reports of standard medical associations. This chapter also explained two scenarios in which risk parameters and unknown parameters for different blood sugar and BP levels were considered. In the first scenario, the risk levels were tested and the summarized outputs of different patients were presented to see the approximate values expected and achieved during the execution of our model. In the second scenario, the unknown parameter was alerted to the doctor’s screen using the triggering operation, which will update on all unknown parameters every five seconds. The prediction process of this proposed approach revealed that patient information can be processed in little time without the need for any kind of medical experts. This in turn can work as an early risk warning for healthcare professionals to solve the problems that come at runtime. All changes in patient health conditions can be monitored, predicted and mitigated to produce feedback and alerts in the database as well as to patients.

Chapter 8: Conclusion and Future Work

Objectives

- To summarise this research
- To highlight the original contribution to knowledge
- To provide a general overview of future research

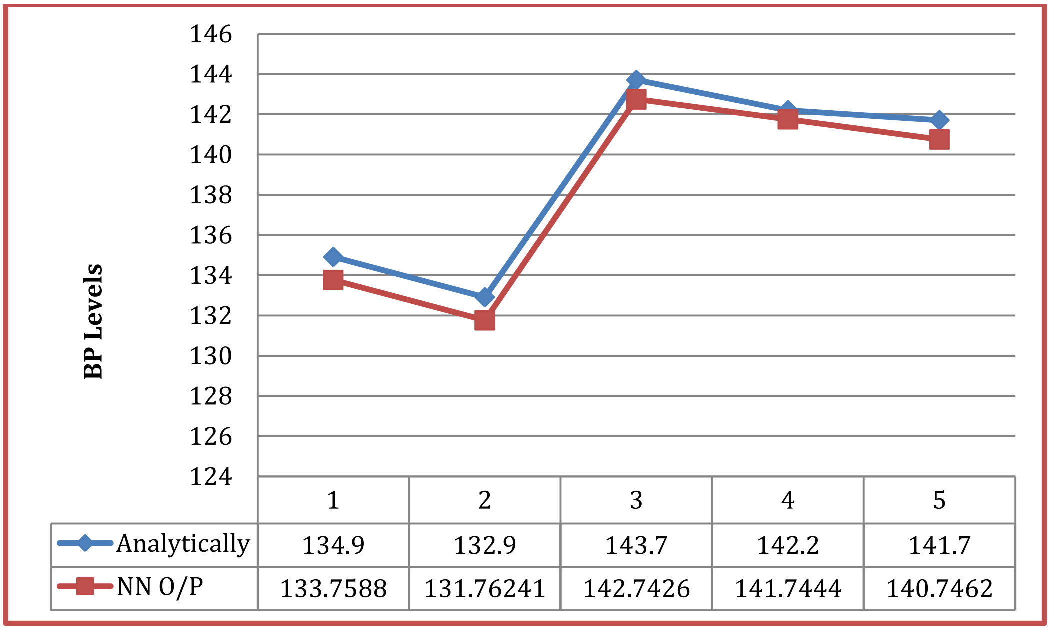
8.1. Summary of Thesis

The proposed early risk warning system approach for healthcare can provide a faster method of identifying risks at runtime. The limitations of risk management can be reduced in healthcare (as discussed in Chapter 2) by adding the advantages of the ERWS proposed in this research. The mitigation of a risk and time taken for the mitigation has previously been quite high. In this situation, some patients suffer badly, even putting their lives at risk by the time the problem was mitigated. This delay was due to the need for longer observation times to record patient health status (BP and blood sugar levels) at regular intervals. Such demands keep doctors and technicians on their toes to avoid errors while recording the values. For these reasons, the objectives of this research (as discussed in Chapter 1) are to provide a solution for predicting risk at a faster rate. In the proposed approach, patient health levels (BP and blood sugar values of 200 patients) are stored in a database directly from the records (collected from monitoring devices as mentioned in Chapters 3 and 4) of a hospital in Saudi Arabia. These values were processed using the proposed approach using neural networks to predict the status of patient health condition.

A computational model and prototype of the proposed approach were developed to test the interactions between different components and attributes (as seen in Chapters 3 and 6, respectively). The development of the architecture and its implementation for risk prediction and the checker process for checking the input values from the hospital environment were seen in detail in Chapters 4 and 5. These chapters revealed the key areas of the risk prediction process and runtime monitoring within the hospital environment using neural networks. The case study (as discussed in Chapter 7) explored the response/nature of the RPC and Checker components for different input parameters (with risk levels, unknown parameter and no risk levels). The application of the trigger at different levels to communicate feedback for patients and doctors by generating alerts was also seen in Chapter 7.

8.2. Evaluation with Related Work

Using NN almost provided the desired outputs compared with analytically calculated values. To evaluate the performance of the proposed approach, the average value will generally be calculated using general analytical techniques. However, these methods are not applicable when the system is considered at runtime, as the input parameters will change continuously. Taking average values of such a large range of numbers, which changes regularly, is difficult. Hence, the role of neural networks in this research to predict the appropriate level of different health parameters is vital. The outcomes of the proposed approach delivered the expected results and comparisons between expected values with neural networks outputs have not shown any big difference (see Table 12). A plot was drawn for five patients for the outputs from NN, and analytically calculated values are shown in Figure 38.



	1	2	3	4	5
Analytically	134.9	132.9	143.7	142.2	141.7
NN O/P	133.7588	131.76241	142.7426	141.7444	140.7462

Figure 38: Results for NN outputs Vs Analytical Calculations for High BP

	High BP		Low BP		Sugar Before Meals		Sugar after meals	
Patient ID	**Analytically**	**NN O/P**	**Analytically**	**NN O/P**	**Analytically**	**NN O/P**	**Analytically**	**NN O/P**
102	134.9	133.7588	80.6	79.856003	107.2	106.8074	169.7	185.66521
114	132.9	131.76241	79.2	78.857803	106.5	105.8092	186.8	185.665
182	143.7	142.7426	80.8	79.856003	82.5	81.852402	203.23	202.6346
292	142.2	141.7444	80.8	79.856003	124.1	123.7768	201.8	221.6004
299	141.7	140.7462	81.2	80.854202	160.3	160.71021	467	466.15939

Table 12: Results for outputs of NN Vs Analytical calculations for four parameters

The above table shows that NN outputs almost deliver the outputs, which are approximately equal to the analytical values after taking the average values (as discussed in section 2.5.4).

8.3. Contribution

The main contribution of the proposed research is the development of an early risk warning system approach to provide better treatment for diabetic patients at runtime. The changes in patient health conditions were monitored and the predicted risks were communicated to patients with appropriate feedback.

Chapter 3 provided a computational model suitable for the hospital environment at runtime. This model considers different parameters like the blood sugar levels and BP levels of a diabetic patient.

Chapter 4 designed the architecture suitable for healthcare to predict and mitigate risks in time to avoid maximum damage to the patient. The risk prediction and checker process time is extensively reduced compared to traditional healthcare.

Chapter 5 implemented the risk prediction component using the back propagation algorithm. This helps the checker to compare the outputs with the ideal values of the database to generate alerts and communication based on health status.

Chapter 6 implemented a prototype suitable for the proposed approach to an early risk warning system. The triggering technique using SQL to generate alerts was established for producing the feedback between patients and hospital management teams.

Chapter 7 obtained results with our proposed approach by evaluating the scenarios with different risk conditions monitored by the proposed ERWS. The outcomes of these results delivered satisfactory outputs as seen in sections 7.3, 7.4 and 8.2.

8.4. Achieving Success Criteria

The answer for the research questions in section 1.4 towards proposing an approach for early risk warning system (ERWS) approach is the designed, implemented and evaluated system with results proven to meet the actual requirement of medical standards. The proposed ERWS approach allows the risk management team and doctors in the hospital to mitigate the predicted results as early as possible to provide better and more suitable treatment for diabetic patients.

- The risk prediction component delivered its outputs to the checker component, and upon identification of a risk, the trigger component alerted patients and doctors.
- This total process was updated to the patient and doctor within five seconds after the recognition of an unknown parameter at runtime. Compared to traditional healthcare methods, this approach provides the health status of patients at a much faster rate. Hence, the overall time to predict risk has been reduced.
- As per the discussion in Chapter 2, the neural networks delivered the assumed results towards predicting the output parameters. The values obtained from the outputs of the neural networks are almost in the range of nearest values (as seen in Table 12).

- The proposed approach delivers a successful early risk warning system appropriate for healthcare at runtime by providing a faster response to unknown parameters and sudden changes in health conditions of a patient.

8.5. Future work

The implemented work was developed based on values obtained from the hospital in Saudi Arabia. The same values can be retrieved and processed to the database directly from the monitoring devices so as to check the patient condition at runtime with live values. The approach in such conditions will be the same, as the training of neural networks needs to be updated only if medical standards define new risk parameters. Otherwise, using the neural networks-based risk prediction component as per the proposed research can be coupled with the monitoring devices of the hospital environment.

Not only blood sugar and BP levels but various other parameters of diabetic patients can also be monitored and tested using the risk prediction component at runtime. This approach is capable of adding additional neural networks layers (as shown in Figure 13) for predicting inputs containing body temperature, body mass index (BMI) and insulin levels of a patient. The principles and working procedure will not change, only the training of layers with ideal conditions need be updated for each parameter based on medical standards.

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Appendix A: Prototype

A.1. Prototype Classes

A.1.1. Patient

Patient is a component implemented using Java and the information of the patient will be loaded by the hospital using manual methods. However, in proposed approach, the patient health parameters will be considered in this research and they will be updated in the database. The information from this class will be applied to sugar and BP classes in the proposed approach.

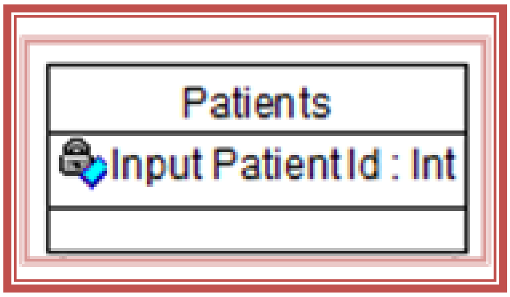

Figure 39: Structure of Patient. java

A.1.2. Sugar and BP

Sugar and BP are the classes in the proposed prototype implemented using java. these classes are connected with risk prediction component and provides the health status of patient with sugar and BP levels. The relevant information of the patients sugar levels and BP levels are stored in the database according to patient details provided with unique patient ID. These classes gets information from the patients, provide the inputs to trains the input vector matrix at risk prediction component and allows the process to run continuously as shown in Figure A.2.

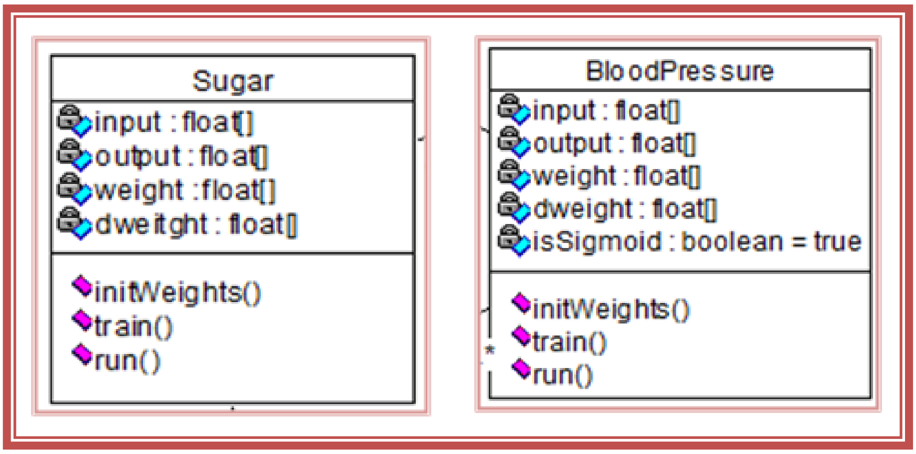

Figure 40: Structure of Sugar.java and BloodPressure.java

A.1.3. Checker

Checker is a class in the proposed prototype implemented using java. It takes the inputs from the prediction component and checks the same with the ideal conditions stored in database. The process of checker is a two way process where the inputs comes and are checked outputs are processed through database for sending the feedbacks to doctors and patients after triggering process.

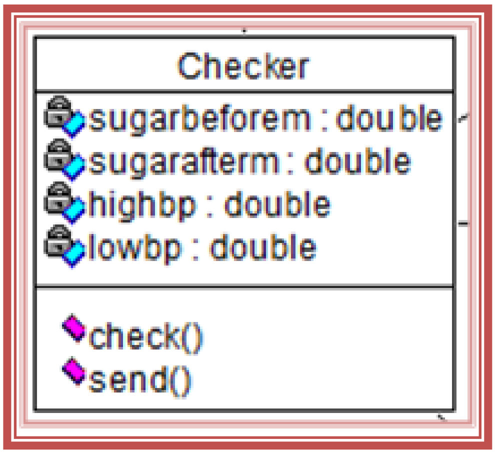

Figure 41: Structure of Checker.java

A.1.4. Trigger

Trigger is a class in the proposed prototype implemented using java. It takes the inputs from the checker component and generates alerts when a risk is identified or even when an unknown parameter is identified. The trigger component will generate the alerts for both patients and doctors continuously. This component is responsible for establishing communication between patient, doctors and hospital team management when a risk or unknown parameter is identified.

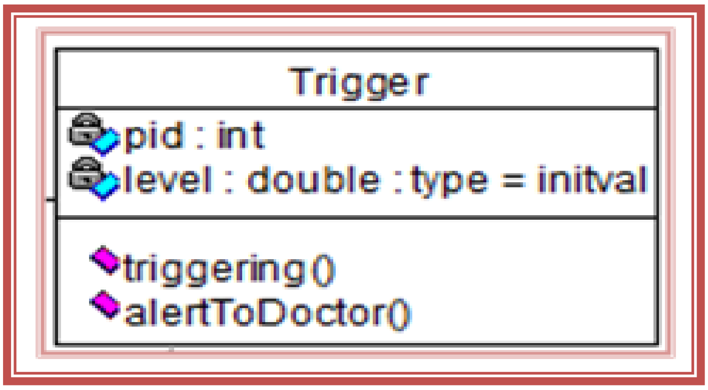

Figure 42: Structure of Trigger.java

A.1.5. Hospital Team Management

Hospital team management is a component implemented using java. This component interacts with the information of all other components in the proposed approach and ensures that the predicted parameters are mitigated to provide the patient with suitable treatment.

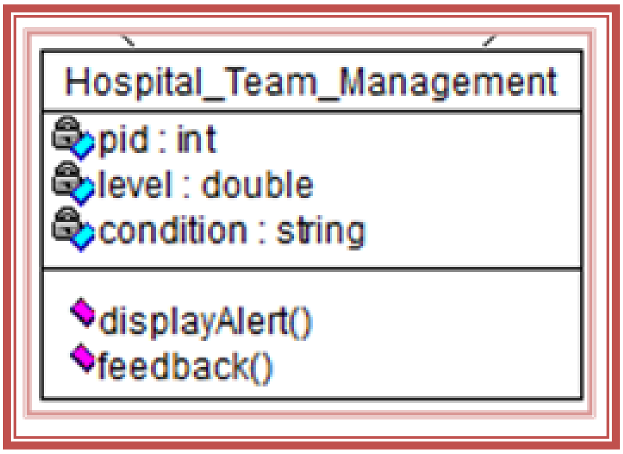

Figure 43: Structure of Hospital_Team_Managment.java

Appendix B: Medical Standards for Diabetic Patients

B.1. Blood glucose/ sugar levels

Diabetes are classified into two types: Type 1 (IDDM: Insulin dependent diabetes mellitus) and Type 2 (NIDDM: non-insulin dependent diabetes mellitus) diabetes [98]. However, there is another third method also is there which generally called as MODY (Maturity onset diabetes of the young). The third one totally based on genetic disorders and is due to inheritance from the parents and family [100].

IDDM is the frequently observed problem for youngsters and it can occur for any age. It also needs insulin treatment for controlling the hyperglycaemic state. NIDDM is generally observed in old aged people and they may need some dietary supplements. IDDM is also considered as Type 1 and NIDDM is known as Type 2 diabetes. Standard values for the glucose levels [98] are given in Figure 44.

	Glucose concentration, mmol/litre (mg/dl)			
	Whole blood		Plasma	
	Venous	Capillary	Venous	Capillary
Diabetes mellitus				
Fasting value	≥ 6.7 (≥ 120)	≥ 6.7 (≥ 120)	≥ 7.8 (≥ 140)	≥ 7.8 (≥ 140)
2 hours after glucose load	≥ 10.0 (≥ 180)	≥ 11.1 (≥ 200)	≥ 11.1 (≥ 200)	≥ 12.2 (≥220)
Impaired glucose Tolerance (IGT)				
Fasting value	< 6.7 (< 120)	< 6.7 (< 120)	< 7.8 (< 140)	< 7.8 (< 140)
2 hours after glucose load	6.7-10.0 (120-180)	7.8-11.1 (140-200)	7.8-11.1 (140-200)	8.9-12.2 (160-220)

Figure 44: Diagnostic values for the oral glucose tolerance test

B.2. Blood pressure levels

The Blood Pressure levels are classified into two ways based on the heart functioning. The pressure generated when heart is contracts is known as Systolic Pressure and if it is relaxed then the pressure is called Diastolic pressure. In simple systolic pressure is known as High BP and diastolic pressure is called as Low BP.

The definitions of blood pressure categories are given by American Heart Association are given here under [87]:

Comment	Systolic	Diastolic	S - D Delta	MAP
Far, Far, Far TOO HIGH Medication Is ABSOLUTELY NECESSARY To Prevent Heart Attack and Stroke	230	135	95	167
	225	130	95	162
	220	130	90	160
	215	125	90	155
	210	125	85	153
	205	120	85	148
	200	120	80	147
	195	115	80	142
	190	115	75	140
	185	110	75	135
Way Too High - Medication Is STRONGLY ADVISED	180	110	70	133
	175	105	70	128
	170	105	65	127
	165	100	65	122
Too High - Most Doctors Will Prescribe Meds	160	100	60	120
	155	95	60	115
	150	95	55	113
Borderline - Some Doctors Will Prescribe Meds	145	90	55	108
	140	90	50	107
	135	85	50	102
Good	130	85	45	100
	125	80	45	95
Very Good	120	80	40	93
	115	75	40	88
	110	70	40	83
Excellent	105	70	35	82
Children and Athletes	100	65	35	77
	95	65	30	75
	90	60	30	70
Too Low - Meds May Be Required To Prevent Fainting (Syncope)	85	55	30	65
	80	55	25	63
	75	50	25	58
	70	50	20	57
Far, Far, Far Too Low - MEDICATION REQUIRED	65	45	20	52
	60	45	15	50
	55	40	15	45
	50	35	15	43
180	60	60	60	60

Figure 45: Shows the Table of Blood Pressure Levels

Appendix C: Real Data of 200 Patients from Saudi Hospital

Kingdome of Saudi Arabia
Ministry of Health
General Directorate of Health
Affairs in Madinah
Al-Ansar Hospital

وزارة الصحة
Ministry of Health

المملكه العربيه السعوديه
وزارة الصحة
المديرية العامه للشئون الصحية في
المدينة المنورة
مستشفى الانصار

September 10, 2013

TO WHOM IT MAY CONCERN

This is to certify that **Mr. Amr Jadi,** a student of PhD from De Montfort University collected the relevant information to conduct his research. He came to us with a list of requirements included with body temperatures, sugar levels and blood pressure levels of different patients. But all these parameters for whole patients are not possible expect the glucose levels of diabetes patients. At the same time he also requested to provide the information of 500 – 1000 patients. However, the hospital management suggested to conduct the research with the information of 200 patients as it was sufficient for this kind of research activities.

He was provided with blood pressure levels and glucose levels of 200 patients' with specified terms and conditions. The information provided to Him must be used only for the research purpose but can not be used elsewhere.

General Director of Patient Affairs

ص ب (٤٤٢٩٧)- المدينه المنورة -المملكة العربية السعوديه- هاتف(٨٣٦٠٢٠٨)-وفاكس(٨٣٦١٣٣٦)

Before Meals										
	October	November	December	January	February	March	April	May	June	July
101	85	70	77	80	80	79	81	86	90	102
102	109	185	76	98	75	86	78	90	160	115
103	110	100	79	96	80	98	75	79	76	119
104	111	80	96	80	100	99	88	96	102	90
105	111	102	95	97	84	86	81	88	90	92
106	118	125	86	98	87	89	87	94	90	85
107	115	119	87	98	94	88	80	81	83	80
108	85	70	77	80	80	79	81	86	90	102
109	86	81	79	80	88	79	82	75	84	83
110	120	104	116	99	87	80	77	79	72	85
111	105	114	98	96	88	84	79	82	97	113
112	135	150	104	109	120	111	142	136	168	175
113	111	96	75	92	85	96	74	82	92	105
114	130	120	154	98	96	91	98	85	102	91
115	125	114	240	230	265	240	261	219	199	165
116	138	152	126	129	144	112	98	93	97	91
117	139	121	136	147	142	125	129	80	86	84
118	75	86	89	92	102	115	79	83	80	84
119	82	85	80	76	90	81	86	76	83	86
120	121	105	114	93	80	90	81	79	86	80
121	112	125	103	98	85	89	80	85	136	141
122	145	118	80	96	80	96	96	92	120	116
123	105	101	80	94	92	93	99	80	86	103
124	114	80	97	85	97	80	75	98	109	98
125	114	125	108	100	136	142	120	150	120	132
126	112	125	103	98	85	89	80	85	136	141
127	108	113	126	104	125	130	120	150	148	160
128	113	126	104	99	86	90	81	86	137	142

129	120	135	128	90	135	120	99	89	102	150
130	106	111	124	102	123	128	118	148	146	158
131	117	132	125	87	132	117	96	86	99	147
132	114	127	105	100	87	91	82	87	138	143
133	104	109	122	100	121	126	116	146	144	156
134	114	129	122	84	129	114	93	83	96	144
135	115	128	106	101	88	92	83	88	139	144
136	102	107	120	98	119	124	114	144	142	154
137	111	126	119	81	126	111	90	80	93	141
138	116	129	107	102	89	93	84	89	140	145
139	100	105	118	96	117	122	112	142	140	152
140	108	123	116	78	123	108	87	77	90	138
141	117	130	108	103	90	94	85	90	141	146
142	98	103	116	94	115	120	110	140	138	150
143	105	120	113	75	120	105	84	74	87	135
144	118	131	109	104	91	95	86	91	142	147
145	118	131	109	104	91	95	86	91	142	147
146	102	117	110	72	117	102	81	71	84	132
147	119	132	110	105	92	96	87	92	143	148
148	116	129	107	102	89	93	84	89	140	145
149	99	114	107	69	114	99	78	68	81	129
150	120	133	111	106	93	97	88	93	144	149
151	114	127	105	100	87	91	82	87	138	143
152	96	111	104	66	111	96	75	65	78	126
153	121	134	112	107	94	98	89	94	145	150
154	112	125	103	98	85	89	80	85	136	141
155	93	108	101	63	108	93	72	62	75	123
156	122	135	113	108	95	99	90	95	146	151
157	110	123	101	96	83	87	78	83	134	139
158	90	105	98	60	105	90	69	60	72	120

159	123	136	114	109	96	100	91	96	147	152
160	108	121	99	94	81	85	76	81	132	137
161	88	103	96	128	103	88	93	78	70	118
162	124	137	115	110	97	101	92	97	148	153
163	106	119	97	92	79	83	74	79	130	135
164	86	101	94	126	101	86	91	76	68	116
165	125	138	116	111	98	102	93	98	149	154
166	104	117	95	90	77	81	72	77	128	133
167	84	99	92	124	99	84	89	74	66	114
168	126	139	117	112	99	103	94	99	150	155
169	102	115	93	88	75	79	70	75	126	131
170	82	97	90	122	97	82	87	72	64	112
171	127	140	118	113	100	104	95	100	151	156
172	100	113	91	86	73	77	68	73	124	129
173	80	95	88	120	95	80	85	70	62	110
174	128	141	119	114	101	105	96	101	152	157
175	98	111	89	84	71	75	66	71	122	127
176	78	93	86	118	93	78	83	68	60	108
177	129	142	120	115	102	106	97	102	153	158
178	96	109	87	82	69	73	64	69	120	125
179	76	91	84	116	91	76	81	66	64	106
180	130	143	121	116	103	107	98	103	154	159
181	94	107	85	80	67	71	62	67	118	123
182	74	89	82	114	89	74	79	64	56	104
183	131	144	122	117	104	108	99	104	155	160
184	92	105	83	78	65	69	60	65	116	121
185	72	87	80	112	87	72	77	62	54	102
186	132	145	123	118	105	109	100	105	156	161
187	90	103	81	76	63	67	58	63	114	119
188	70	85	78	110	85	70	75	60	52	100

189	133	146	124	119	106	110	101	106	157	162
190	88	101	79	74	61	65	56	61	112	117
191	68	83	76	108	83	68	73	58	50	98
192	134	147	125	120	107	111	102	107	158	163
193	86	99	77	72	59	63	54	59	110	115
194	66	81	74	106	81	66	71	56	48	96
195	135	148	126	121	108	112	103	108	159	164
196	84	97	75	70	57	61	52	57	108	113
197	64	79	72	104	79	64	69	54	46	94
198	136	149	127	122	109	113	104	109	160	165
199	82	95	73	68	55	59	50	55	106	111
200	62	77	70	102	77	62	67	52	44	92
201	127	119	126	115	105	116	99	91	80	86
202	96	93	118	130	125	115	140	162	169	180
203	129	135	122	160	122	105	136	130	119	125
204	159	145	148	135	139	133	162	156	137	147
205	128	120	127	116	106	117	100	92	81	87
206	94	91	116	128	123	113	138	160	167	178
207	126	132	119	157	119	102	133	127	116	122
208	158	144	147	134	138	132	161	155	136	146
209	129	121	128	117	107	118	101	93	82	88
210	92	89	114	126	121	111	136	158	165	176
211	123	129	116	154	116	99	130	124	113	119
212	157	143	146	133	137	131	160	154	135	145
213	130	122	129	118	108	119	102	94	83	89
214	90	87	112	124	119	109	134	156	163	174
215	120	126	113	151	113	96	127	121	110	116
216	156	142	145	132	136	130	159	153	134	144
217	131	123	130	119	109	120	103	95	84	90
218	88	85	110	122	117	107	132	154	161	172

219	117	123	110	148	110	93	124	118	107	113
220	155	141	144	131	135	129	158	152	133	143
221	132	124	131	120	110	121	104	96	85	91
222	86	83	108	120	115	105	130	152	159	170
223	114	120	107	145	107	90	121	115	104	110
224	154	140	143	130	134	128	157	151	132	142
225	133	125	132	121	111	122	105	97	86	92
226	118	131	109	104	91	95	86	91	142	147
227	111	117	104	142	104	87	118	112	101	107
228	153	139	142	129	133	127	156	150	131	141
229	134	126	133	122	112	123	106	98	87	93
230	116	129	107	102	89	93	84	89	140	145
231	108	114	101	139	101	84	115	109	98	104
232	152	138	141	128	132	126	155	149	130	140
233	135	127	134	123	113	124	107	99	88	94
234	114	127	105	100	87	91	82	87	138	143
235	105	111	98	136	98	81	112	106	95	101
236	151	137	140	127	131	125	154	148	129	139
237	136	128	135	124	114	125	108	100	89	95
238	112	125	103	98	85	89	80	85	136	141
239	102	108	95	133	95	78	109	103	92	98
240	150	136	139	126	130	124	153	147	128	138
241	137	129	136	125	115	126	109	101	90	96
242	110	123	101	96	83	87	78	83	134	139
243	99	105	92	130	92	75	106	100	89	95
244	149	135	138	125	129	123	152	146	127	137
245	138	130	137	126	116	127	110	102	91	97
246	108	121	99	94	81	85	76	81	132	137
247	97	103	90	128	90	73	104	98	87	93
248	148	134	137	124	128	122	151	145	126	136

249	139	131	138	127	117	128	111	103	92	98
250	106	119	97	92	79	83	74	79	130	135
251	95	101	88	126	88	71	102	96	85	91
252	147	133	136	123	127	121	150	144	125	135
253	140	132	139	128	118	129	112	104	93	99
254	104	117	95	90	77	81	72	77	128	133
255	93	99	86	124	86	69	100	94	83	89
256	146	132	135	122	126	120	149	143	124	134
257	141	133	140	129	119	130	113	105	94	100
258	102	115	93	88	75	79	70	75	126	131
259	91	97	84	122	84	67	98	92	81	87
260	145	131	134	121	125	119	148	142	123	133
261	142	134	141	130	120	131	114	106	95	101
262	100	113	91	86	73	77	68	73	124	129
263	89	95	82	120	82	65	96	90	79	85
264	144	130	133	120	124	118	147	141	122	132
265	143	135	142	131	121	132	115	107	96	102
266	98	111	89	84	71	75	66	71	122	127
267	87	93	80	118	80	63	94	88	77	83
268	143	129	132	119	123	117	146	140	121	131
269	144	136	143	132	122	133	116	108	97	103
270	96	109	87	82	69	73	64	69	120	125
271	85	91	78	116	78	61	92	86	75	81
272	142	128	131	118	122	116	145	139	120	130
273	145	137	144	133	123	134	117	109	98	104
274	94	107	85	80	67	71	62	67	118	123
275	83	89	76	114	76	59	90	84	73	79
276	141	127	130	117	121	115	144	138	119	129
277	146	138	145	134	124	135	118	110	99	105
278	92	105	83	78	65	69	60	65	116	121

279	81	87	74	112	74	57	88	82	71	77
280	140	126	129	116	120	114	143	137	118	128
281	147	139	146	135	125	136	119	111	100	106
282	90	103	81	76	63	67	58	63	114	119
283	79	85	72	110	72	55	86	80	69	75
284	139	125	128	115	119	113	142	136	117	127
285	148	140	147	136	126	137	120	112	101	107
286	88	101	79	74	61	65	56	61	112	117
287	77	83	70	108	70	53	84	78	67	73
288	138	124	127	114	118	112	141	135	116	126
289	149	141	148	137	127	138	121	113	102	108
290	86	99	77	72	59	63	54	59	110	115
291	75	81	68	106	68	51	82	76	65	71
292	137	123	126	113	117	111	140	134	115	125
293	150	142	149	138	128	139	122	114	103	109
294	84	97	75	70	57	61	52	57	108	113
295	73	79	66	104	66	49	80	74	63	69
296	136	122	125	112	116	110	139	133	114	124
297	151	143	150	139	129	140	123	115	104	110
298	82	95	73	68	55	59	50	55	106	111
299	150	160	159	165	166	160	157	162	163	161
300	135	121	124	111	115	109	138	132	113	123

After Meals										
	October	November	December	January	February	March	April	May	June	July
101	152	246	147	242	174	124	92	142	193	225
102	165	170	140	250	195	164	188	320	160	115
103	152	289	257	242	198	152	166	142	193	225
104	147	159	150	180	169	200	160	157	166	149
105	200	192	219	152	160	140	160	149	169	179
106	225	250	146	150	149	166	192	140	160	111
107	246	199	152	160	159	135	146	149	151	163
108	155	159	165	138	170	159	157	164	152	171
109	170	159	162	148	164	169	155	164	158	146
110	356	299	268	189	160	159	157	145	159	188
111	148	142	143	135	150	156	129	136	162	159
112	122	156	186	194	169	209	215	327	228	302
113	192	209	216	196	198	197	207	189	179	162
114	145	154	149	175	163	198	165	183	175	152
115	191	215	320	345	362	312	369	315	258	287
116	266	254	249	298	190	168	162	158	169	190
117	251	241	235	271	215	224	216	150	158	160
118	156	160	164	147	160	158	164	163	158	164
119	169	163	164	159	166	159	149	139	160	175
120	256	264	269	159	168	162	135	137	155	196
121	152	246	147	242	174	124	92	142	193	225
122	175	150	160	223	189	198	179	305	190	111
123	165	300	260	240	202	198	159	168	169	200
124	156	147	156	190	150	200	160	157	166	149
125	202	196	200	153	201	236	198	189	190	196
126	253	243	289	243	359	256	159	212	203	219
127	353	340	325	360	321	259	246	262	230	235
128	298	267	226	258	213	225	238	249	294	222

129	254	244	290	244	360	257	160	213	204	220
130	351	338	323	358	319	257	244	260	228	233
131	295	264	223	255	210	222	235	246	291	219
132	255	245	291	245	361	258	161	214	205	221
133	349	336	321	356	317	255	242	258	226	231
134	292	261	220	252	207	219	232	243	288	216
135	256	246	292	246	362	259	162	215	206	222
136	347	334	319	354	315	253	240	256	224	229
137	289	258	217	249	204	216	229	240	285	213
138	257	247	293	247	363	260	163	216	207	223
139	345	332	317	352	313	251	238	254	222	227
140	286	255	214	246	201	213	226	237	282	210
141	258	248	294	248	364	261	164	217	208	224
142	343	330	315	350	311	249	236	252	220	225
143	283	252	211	243	198	210	223	234	279	207
144	259	249	295	249	365	262	165	218	209	225
145	343	330	315	350	311	249	236	252	220	225
146	280	249	208	240	195	207	220	231	276	204
147	260	250	296	250	366	263	166	219	210	226
148	354	326	311	346	307	245	232	248	216	221
149	277	246	205	237	192	204	217	228	273	201
150	261	251	297	251	367	264	167	220	211	227
151	352	324	309	344	305	243	230	246	214	219
152	274	243	202	234	189	201	214	225	270	198
153	262	252	298	252	368	265	168	221	212	228
154	350	322	307	342	303	241	228	244	212	217
155	271	240	199	231	186	198	211	222	267	195
156	263	253	299	253	369	266	169	222	213	229
157	348	320	305	340	301	239	226	242	210	215
158	268	237	196	228	183	195	208	219	264	192

159	264	254	300	254	370	267	170	223	214	230
160	346	318	303	338	299	237	224	240	208	213
161	266	235	194	226	181	193	206	217	262	190
162	265	255	301	255	371	268	171	224	215	231
163	344	316	301	336	297	235	222	238	206	211
164	264	233	192	224	179	191	204	215	260	188
165	266	256	302	256	372	269	172	225	216	232
166	342	314	299	334	295	233	220	236	204	209
167	262	231	190	222	177	189	202	213	258	186
168	267	257	303	257	373	270	173	226	217	233
169	340	312	297	332	293	231	218	234	202	207
170	260	229	188	220	175	187	200	211	256	184
171	268	258	304	258	374	271	174	227	218	234
172	338	310	295	330	291	229	216	232	200	205
173	258	227	186	218	173	185	198	209	254	182
174	269	259	305	259	375	272	175	228	219	235
175	336	308	293	328	289	227	214	230	198	203
176	256	225	184	216	171	183	196	207	252	180
177	270	260	306	260	376	273	176	229	220	236
178	334	306	291	326	287	225	212	228	196	201
179	254	223	182	214	169	181	194	205	250	178
180	271	261	307	261	377	274	177	230	221	237
181	332	304	289	324	285	223	210	226	194	199
182	252	221	180	212	167	179	192	203	248	176
183	272	262	308	262	378	275	178	231	222	238
184	330	302	287	322	283	221	208	224	192	197
185	250	219	178	210	165	177	190	201	246	174
186	273	263	309	263	379	276	179	232	223	239
187	328	300	285	320	281	219	206	222	190	195
188	248	217	176	208	163	175	188	199	244	172

189	274	264	310	264	380	277	180	233	224	240
190	326	298	283	318	279	217	204	220	188	193
191	246	215	174	206	161	173	186	197	242	170
192	275	265	311	265	381	278	181	234	225	241
193	324	296	281	316	277	215	202	218	186	191
194	244	213	172	204	159	171	184	195	240	168
195	276	266	312	266	382	279	182	235	226	242
196	322	294	279	314	275	213	200	216	184	189
197	242	211	170	202	157	169	182	193	238	166
198	277	267	313	267	383	280	183	236	227	243
199	320	292	277	312	273	211	198	214	182	187
200	240	209	168	200	155	167	180	191	236	164
201	190	193	209	225	260	246	261	280	312	345
202	290	281	279	250	243	240	236	228	219	230
203	297	265	236	268	223	229	243	260	290	246
204	292	260	231	263	218	250	264	298	269	315
205	191	194	210	226	261	247	262	281	313	346
206	288	279	277	248	241	238	234	226	217	228
207	294	262	233	265	220	226	240	257	287	243
208	290	258	229	261	216	248	262	296	267	313
209	192	195	211	227	262	248	263	282	314	347
210	286	277	275	246	239	236	232	224	215	226
211	291	259	230	262	217	223	237	254	284	240
212	288	256	227	259	214	246	260	294	265	311
213	193	196	212	228	263	249	264	283	315	348
214	284	275	273	244	237	234	230	222	213	224
215	288	256	227	259	214	220	234	251	281	237
216	286	254	225	257	212	244	258	292	263	309
217	194	197	213	229	264	250	265	284	316	349
218	282	273	271	242	235	232	228	220	211	222

219	285	253	224	256	211	217	231	248	278	234
220	284	252	223	255	210	242	256	290	261	307
221	195	198	214	230	265	251	266	285	317	350
222	280	271	269	240	233	230	226	218	209	220
223	282	250	221	253	208	214	228	245	275	231
224	282	250	221	253	208	240	254	288	259	305
225	196	199	215	231	266	252	267	286	318	351
226	278	269	267	238	231	228	224	216	207	218
227	279	247	218	250	205	211	225	242	272	228
228	280	248	219	251	206	238	252	286	257	303
229	197	200	216	232	267	253	268	287	319	352
230	276	267	265	236	229	226	222	214	205	216
231	276	244	215	247	202	208	222	239	269	225
232	278	246	217	249	204	236	250	284	255	301
233	198	201	217	233	268	254	269	288	320	353
234	274	265	263	234	227	224	220	212	203	214
235	273	241	212	244	199	205	219	236	266	222
236	276	244	215	247	202	234	248	282	253	299
237	199	202	218	234	269	255	270	289	321	354
238	272	263	261	232	225	222	218	210	201	212
239	270	238	209	241	196	202	216	233	263	219
240	274	242	213	245	200	232	246	280	251	297
241	200	203	219	235	270	256	271	290	322	355
242	270	261	259	230	223	220	216	208	199	210
243	267	235	206	238	193	199	213	230	260	216
244	272	240	211	243	198	230	244	278	249	295
245	201	204	220	236	271	257	272	291	323	356
246	268	259	257	228	221	218	214	206	197	208
247	265	233	204	236	191	197	211	228	258	214
248	270	238	209	241	196	228	242	276	247	293

249	202	205	221	237	272	258	273	292	324	357
250	266	257	255	226	219	216	212	204	195	206
251	263	231	202	234	189	195	209	226	256	212
252	268	236	207	239	194	226	240	274	245	291
253	203	206	222	238	273	259	274	293	325	358
254	264	255	253	224	217	214	210	202	193	204
255	261	229	200	232	187	193	207	224	254	210
256	266	234	205	237	192	224	238	272	243	289
257	204	207	223	239	274	260	275	294	326	359
258	262	253	251	222	215	212	208	200	191	202
259	259	227	198	230	185	191	205	222	252	208
260	264	232	203	235	190	222	236	270	241	287
261	205	208	224	240	275	261	276	295	327	360
262	260	251	249	220	213	210	206	198	189	200
263	257	225	196	228	183	189	203	220	250	206
264	262	230	201	233	188	220	234	268	239	285
265	206	209	225	241	276	262	277	296	328	361
266	258	249	247	218	211	208	204	196	187	198
267	255	223	194	226	181	187	201	218	248	204
268	260	228	199	231	186	218	232	266	237	283
269	207	210	226	242	277	263	278	297	329	362
270	256	247	245	216	209	206	202	194	185	196
271	253	221	192	224	179	185	199	216	246	202
272	258	226	197	229	184	216	230	264	235	281
273	208	211	227	243	278	264	279	298	330	363
274	254	245	243	214	207	204	200	192	183	194
275	251	219	190	222	177	183	197	214	244	200
276	256	224	195	227	182	214	228	262	233	279
277	209	212	228	244	279	265	280	299	331	364
278	252	243	241	212	205	202	198	190	181	192

279	249	217	188	220	175	181	195	212	242	198
280	254	222	193	225	180	212	226	260	231	277
281	210	213	229	245	280	266	281	300	332	365
282	250	241	239	210	203	200	196	188	179	190
283	247	215	186	218	173	179	193	210	240	196
284	252	220	191	223	178	210	224	258	229	275
285	211	214	230	246	281	267	282	301	333	366
286	248	239	237	208	201	198	194	186	177	188
287	245	213	184	216	171	177	191	208	238	194
288	250	218	189	221	176	208	222	256	227	273
289	212	215	231	247	282	268	283	302	334	367
290	246	237	235	206	199	196	192	184	175	186
291	243	211	182	214	169	175	189	206	236	192
292	248	216	187	219	174	206	220	254	225	271
293	213	216	232	248	283	269	284	303	335	368
294	244	235	233	204	197	194	190	182	173	184
295	241	209	180	212	167	173	187	204	234	190
296	246	214	185	217	172	204	218	252	223	269
297	214	217	233	249	284	270	285	304	336	369
298	242	233	231	202	195	192	188	180	171	182
299	239	207	178	210	165	171	185	202	232	188
300	244	212	183	215	170	202	216	250	221	267

High Blood Pressure Levels										
	October	November	December	January	February	March	April	May	June	July
101	120	140	154	140	151	140	164	142	125	124
102	140	135	140	135	144	135	120	125	140	135
103	135	150	135	150	120	150	140	147	135	125
104	150	140	150	119	140	119	135	120	120	126
105	119	135	119	150	135	150	154	144	140	135
106	140	150	120	135	150	119	128	135	139	120
107	135	162	148	140	138	135	130	145	150	140
108	150	135	135	135	135	150	140	119	119	135
109	119	150	140	150	150	119	135	129	138	150
110	123	119	135	140	124	145	150	130	136	127
111	150	140	150	119	140	119	135	120	120	126
112	119	135	119	150	135	150	154	144	140	135
113	119	150	140	150	150	119	135	129	138	150
114	123	119	135	140	124	145	150	130	136	127
115	140	150	120	135	150	119	128	135	139	120
116	120	140	154	140	151	140	164	142	125	124
117	140	135	140	135	144	135	120	125	140	135
118	135	150	135	150	120	150	140	147	135	125
119	135	150	135	150	120	150	140	147	135	125
120	150	140	150	119	140	119	135	120	120	126
121	162	148	140	138	135	130	145	135	140	135
122	135	135	135	135	150	140	119	150	135	150
123	150	140	150	150	119	135	129	140	150	119
124	119	135	140	124	145	150	130	135	119	150
125	140	150	119	140	119	135	120	150	120	135
126	135	119	150	135	150	154	144	162	148	140

127	150	140	150	150	119	135	129	135	135	135
128	119	135	140	124	145	150	130	150	140	150
129	150	120	135	150	119	128	135	119	135	140
130	162	148	140	138	135	130	145	140	150	119
131	135	135	135	135	150	140	119	135	119	150
132	150	140	150	150	119	135	129	150	140	150
133	119	135	140	124	145	150	130	119	135	140
134	140	150	119	140	119	135	120	150	140	150
135	135	119	150	135	150	154	144	119	135	140
136	150	140	150	150	119	135	129	150	120	135
137	119	135	140	124	145	150	130	140	154	140
138	150	120	135	150	119	128	135	135	140	135
139	140	154	140	151	140	164	142	150	135	150
140	135	140	135	144	135	120	125	150	135	150
141	150	135	150	120	150	140	147	140	150	119
142	150	135	150	120	150	140	147	148	140	138
143	140	150	119	140	119	135	120	135	135	135
144	148	140	138	135	130	145	135	140	150	150
145	135	135	135	150	140	119	150	135	140	124
146	135	144	135	120	125	140	120	150	119	140
147	150	120	150	140	147	135	140	119	150	135
148	119	140	119	135	120	120	135	140	150	150
149	150	135	150	154	144	140	150	135	140	124
150	135	150	119	128	135	139	120	120	135	150
151	140	138	135	130	145	150	140	148	140	138
152	135	135	150	140	119	119	135	135	135	135
153	150	150	119	135	129	138	154	140	150	150
154	140	124	145	150	130	136	128	135	140	124

155	119	140	119	135	120	120	130	150	119	140
156	150	135	150	154	144	140	140	119	150	135
157	150	150	119	135	129	138	135	140	150	150
158	140	124	145	150	130	136	150	135	140	124
159	135	150	119	128	135	139	135	120	135	150
160	140	151	140	164	142	125	154	154	140	151
161	119	135	119	150	135	150	154	144	140	135
162	140	150	120	135	150	119	128	135	139	120
163	135	162	148	140	138	135	130	145	150	140
164	150	135	135	135	135	150	140	119	119	135
165	119	150	140	150	150	119	135	129	138	150
166	123	119	135	140	124	145	150	130	136	127
167	150	140	150	119	140	119	135	120	120	126
168	119	135	119	150	135	150	154	144	140	135
169	119	150	140	150	150	119	135	129	138	150
170	123	119	135	140	124	145	150	130	136	127
171	140	150	120	135	150	119	128	135	139	120
172	120	140	154	140	151	140	164	142	125	124
173	140	135	140	135	144	135	120	125	140	135
174	135	150	135	150	120	150	140	147	135	125
175	135	150	135	150	120	150	140	147	135	125
176	150	140	150	119	140	119	135	120	120	126
177	162	148	140	138	135	130	145	135	140	135
178	135	135	135	135	150	140	119	150	135	150
179	150	140	150	150	119	135	129	140	150	119
180	119	135	140	124	145	150	130	135	119	150
181	140	150	119	140	119	135	120	150	120	135
182	135	119	150	135	150	154	144	162	148	140

183	150	140	150	150	119	135	129	135	135	135
184	119	135	140	124	145	150	130	150	140	150
185	150	120	135	150	119	128	135	119	135	140
186	162	148	140	138	135	130	145	140	150	119
187	135	135	135	135	150	140	119	135	119	150
188	150	140	150	150	119	135	129	150	140	150
189	119	135	140	124	145	150	130	119	135	140
190	140	150	119	140	119	135	120	150	140	150
191	135	119	150	135	150	154	144	119	135	140
192	150	140	150	150	119	135	129	150	120	135
193	119	135	140	124	145	150	130	140	154	140
194	150	120	135	150	119	128	135	135	140	135
195	140	154	140	151	140	164	142	150	135	150
196	135	140	135	144	135	120	125	150	135	150
197	150	135	150	120	150	140	147	140	150	119
198	150	135	150	120	150	140	147	148	140	138
199	140	150	119	140	119	135	120	135	135	135
200	148	140	138	135	130	145	135	140	150	150
201	135	135	135	150	140	119	150	135	140	124
202	135	144	135	120	125	140	120	150	119	140
203	150	120	150	140	147	135	140	119	150	135
204	119	140	119	135	120	120	135	140	150	150
205	150	135	150	154	144	140	150	135	140	124
206	135	150	119	128	135	139	120	120	135	150
207	140	138	135	130	145	150	140	148	140	138
208	135	135	150	140	119	119	135	135	135	135
209	150	150	119	135	129	138	154	140	150	150
210	140	124	145	150	130	136	128	135	140	124

211	119	140	119	135	120	120	130	150	119	140
212	150	135	150	154	144	140	140	119	150	135
213	150	150	119	135	129	138	135	140	150	150
214	140	135	140	135	144	135	120	125	140	135
215	135	150	135	150	120	150	140	147	135	125
216	135	150	135	150	120	150	140	147	135	125
217	150	140	150	119	140	119	135	120	120	126
218	162	148	140	138	135	130	145	135	140	135
219	135	135	135	135	150	140	119	150	135	150
220	150	140	150	150	119	135	129	140	150	119
221	119	135	140	124	145	150	130	135	119	150
222	140	150	119	140	119	135	120	150	120	135
223	135	119	150	135	150	154	144	162	148	140
224	150	140	150	150	119	135	129	135	135	135
225	119	135	140	124	145	150	130	150	140	150
226	150	120	135	150	119	128	135	119	135	140
227	162	148	140	138	135	130	145	140	150	119
228	135	135	135	135	150	140	119	135	119	150
229	150	140	150	150	119	135	129	150	140	150
230	119	135	140	124	145	150	130	119	135	140
231	140	150	119	140	119	135	120	150	140	150
232	135	119	150	135	150	154	144	119	135	140
233	150	140	150	150	119	135	129	150	120	135
234	119	135	140	124	145	150	130	140	154	140
235	150	120	135	150	119	128	135	135	140	135
236	140	154	140	151	140	164	142	150	135	150
237	135	140	135	144	135	120	125	150	135	150
238	150	135	150	120	150	140	147	140	150	119

239	150	135	150	120	150	140	147	148	140	138
240	140	150	119	140	119	135	120	135	135	135
241	119	135	119	150	135	150	154	144	140	135
242	140	150	120	135	150	119	128	135	139	120
243	135	162	148	140	138	135	130	145	150	140
244	150	135	135	135	135	150	140	119	119	135
245	119	150	140	150	150	119	135	129	138	150
246	123	119	135	140	124	145	150	130	136	127
247	119	135	119	150	135	150	154	144	140	135
248	119	135	119	150	135	150	154	144	140	135
249	140	150	120	135	150	119	128	135	139	120
250	135	162	148	140	138	135	130	145	150	140
251	150	135	135	135	135	150	140	119	119	135
252	119	150	140	150	150	119	135	129	138	150
253	123	119	135	140	124	145	150	130	136	127
254	150	140	150	119	140	119	135	120	120	126
255	119	135	119	150	135	150	154	144	140	135
256	119	150	140	150	150	119	135	129	138	150
257	123	119	135	140	124	145	150	130	136	127
258	140	150	120	135	150	119	128	135	139	120
259	120	140	154	140	151	140	164	142	125	124
260	140	135	140	135	144	135	120	125	140	135
261	135	150	135	150	120	150	140	147	135	125
262	135	150	135	150	120	150	140	147	135	125
263	150	140	150	119	140	119	135	120	120	126
264	162	148	140	138	135	130	145	135	140	135
265	135	135	135	135	150	140	119	150	135	150
266	150	140	150	150	119	135	129	140	150	119

267	119	135	140	124	145	150	130	135	119	150
268	140	150	119	140	119	135	120	150	120	135
269	135	119	150	135	150	154	144	162	148	140
270	150	140	150	150	119	135	129	135	135	135
271	119	135	140	124	145	150	130	150	140	150
272	150	120	135	150	119	128	135	119	135	140
273	162	148	140	138	135	130	145	140	150	119
274	135	135	135	135	150	140	119	135	119	150
275	150	140	150	150	119	135	129	150	140	150
276	119	135	140	124	145	150	130	119	135	140
277	140	150	119	140	119	135	120	150	140	150
278	135	119	150	135	150	154	144	119	135	140
279	150	140	150	150	119	135	129	150	120	135
280	119	135	140	124	145	150	130	140	154	140
281	150	120	135	150	119	128	135	135	140	135
282	140	154	140	151	140	164	142	150	135	150
283	135	140	135	144	135	120	125	150	135	150
284	150	135	150	120	150	140	147	140	150	119
285	150	135	150	120	150	140	147	148	140	138
286	140	150	119	140	119	135	120	135	135	135
287	148	140	138	135	130	145	135	140	150	150
288	135	135	135	150	140	119	150	135	140	124
289	135	144	135	120	125	140	120	150	119	140
290	150	120	150	140	147	135	140	119	150	135
291	119	140	119	135	120	120	135	140	150	150
292	150	135	150	154	144	140	150	135	140	124
293	135	150	119	128	135	139	120	120	135	150
294	140	138	135	130	145	150	140	148	140	138

295	135	135	150	140	119	119	135	135	135	135
296	150	150	119	135	129	138	154	140	150	150
297	140	124	145	150	130	136	128	135	140	124
298	119	140	119	135	120	120	130	150	119	140
299	150	135	150	154	144	140	140	119	150	135
300	150	150	119	135	129	138	135	140	150	150

Low Blood Pressure Levels										
	October	November	December	January	February	March	April	May	June	July
101	80	82	70	82	90	82	90	79	80	77
102	82	79	82	79	80	79	80	80	82	83
103	79	88	79	88	80	88	82	84	79	80
104	88	82	88	75	82	75	79	80	80	89
105	75	79	75	75	79	88	85	88	86	83
106	82	88	80	79	88	75	78	79	79	80
107	79	82	82	82	82	79	79	88	88	82
108	88	79	79	79	79	88	82	75	75	79
109	75	88	82	88	88	75	79	80	82	88
110	80	75	79	82	76	75	88	78	80	79
111	88	82	88	75	82	75	79	80	80	89
112	75	79	75	75	79	88	85	88	86	83
113	75	88	82	88	88	75	79	80	82	88
114	80	75	79	82	76	75	88	78	80	79
115	82	88	80	79	88	75	78	79	79	80
116	80	82	70	82	90	82	90	79	80	77
117	82	79	82	79	80	79	80	80	82	83
118	79	88	79	88	80	88	82	84	79	80
119	82	88	80	79	88	75	78	79	79	80
120	79	82	82	82	82	79	79	88	88	82
121	88	79	79	79	79	88	82	75	75	79
122	75	88	82	88	88	75	79	80	82	88
123	80	75	79	82	76	75	88	78	80	79
124	88	82	88	75	82	75	79	80	80	89
125	75	79	75	75	79	88	85	88	86	83
126	75	88	82	88	88	75	79	80	82	88

127	80	75	79	82	76	75	88	78	80	79
128	82	88	80	79	88	75	78	79	79	80
129	80	82	70	82	90	82	90	79	80	77
130	82	79	82	79	80	79	80	80	82	83
131	75	88	82	88	88	75	79	80	82	88
132	80	75	79	82	76	75	88	78	80	79
133	88	82	88	75	82	75	79	80	80	89
134	75	79	75	75	79	88	85	88	86	83
135	75	88	82	88	88	75	79	80	82	88
136	80	75	79	82	76	75	88	78	80	79
137	82	88	80	79	88	75	78	79	79	80
138	82	88	80	79	88	75	78	79	79	80
139	79	82	82	82	82	79	79	88	88	82
140	88	79	79	79	79	88	82	75	75	79
141	75	88	82	88	88	75	79	80	82	88
142	80	75	79	82	76	75	88	78	80	79
143	88	82	88	75	82	75	79	80	80	89
144	75	79	75	75	79	88	85	88	86	83
145	75	88	82	88	88	75	79	80	82	88
146	80	75	79	82	76	75	88	78	80	79
147	82	88	80	79	88	75	78	79	79	80
148	80	82	70	82	90	82	90	79	80	77
149	82	79	82	79	80	79	80	80	82	83
150	75	79	75	75	79	88	85	88	86	83
151	75	88	82	88	88	75	79	80	82	88
152	79	82	82	82	82	79	79	88	88	82
153	88	79	79	79	79	88	82	75	75	79
154	75	88	82	88	88	75	79	80	82	88

155	80	75	79	82	76	75	88	78	80	79
156	88	82	88	75	82	75	79	80	80	89
157	75	79	75	75	79	88	85	88	86	83
158	75	88	82	88	88	75	79	80	82	88
159	80	75	79	82	76	75	88	78	80	79
160	82	88	80	79	88	75	78	79	79	80
161	80	82	70	82	90	82	90	79	80	77
162	82	79	82	79	80	79	80	80	82	83
163	79	88	79	88	80	88	82	84	79	80
164	82	88	80	79	88	75	78	79	79	80
165	79	82	82	82	82	79	79	88	88	82
166	88	79	79	79	79	88	82	75	75	79
167	75	88	82	88	88	75	79	80	82	88
168	80	75	79	82	76	75	88	78	80	79
169	88	82	88	75	82	75	79	80	80	89
170	75	79	75	75	79	88	85	88	86	83
171	75	88	82	88	88	75	79	80	82	88
172	80	75	79	82	76	75	88	78	80	79
173	82	88	80	79	88	75	78	79	79	80
174	80	82	70	82	90	82	90	79	80	77
175	82	79	82	79	80	79	80	80	82	83
176	75	88	82	88	88	75	79	80	82	88
177	80	75	79	82	76	75	88	78	80	79
178	88	82	88	75	82	75	79	80	80	89
179	75	79	75	75	79	88	85	88	86	83
180	75	88	82	88	88	75	79	80	82	88
181	80	75	79	82	76	75	88	78	80	79
182	82	88	80	79	88	75	78	79	79	80

183	82	88	80	79	88	75	78	79	79	80
184	79	82	82	82	82	79	79	88	88	82
185	88	79	79	79	79	88	82	75	75	79
186	75	88	82	88	88	75	79	80	82	88
187	80	75	79	82	76	75	88	78	80	79
188	88	82	88	75	82	75	79	80	80	89
189	75	79	75	75	79	88	85	88	86	83
190	75	88	82	88	88	75	79	80	82	88
191	80	75	79	82	76	75	88	78	80	79
192	82	88	80	79	88	75	78	79	79	80
193	80	82	70	82	90	82	90	79	80	77
194	82	79	82	79	80	79	80	80	82	83
195	75	79	75	75	79	88	85	88	86	83
196	75	88	82	88	88	75	79	80	82	88
197	80	75	79	82	76	75	88	78	80	79
198	82	88	80	79	88	75	78	79	79	80
199	80	82	70	82	90	82	90	79	80	77
200	82	79	82	79	80	79	80	80	82	83
201	75	88	82	88	88	75	79	80	82	88
202	80	75	79	82	76	75	88	78	80	79
203	88	82	88	75	82	75	79	80	80	89
204	75	79	75	75	79	88	85	88	86	83
205	75	88	82	88	88	75	79	80	82	88
206	80	75	79	82	76	75	88	78	80	79
207	82	88	80	79	88	75	78	79	79	80
208	80	82	70	82	90	82	90	79	80	77
209	82	79	82	79	80	79	80	80	82	83
210	75	79	75	75	79	88	85	88	86	83

211	75	88	82	88	88	75	79	80	82	88
212	80	75	79	82	76	75	88	78	80	79
213	82	88	80	79	88	75	78	79	79	80
214	80	82	70	82	90	82	90	79	80	77
215	82	79	82	79	80	79	80	80	82	83
216	75	88	82	88	88	75	79	80	82	88
217	80	75	79	82	76	75	88	78	80	79
218	88	82	88	75	82	75	79	80	80	89
219	75	79	75	75	79	88	85	88	86	83
220	75	88	82	88	88	75	79	80	82	88
221	80	75	79	82	76	75	88	78	80	79
222	82	88	80	79	88	75	78	79	79	80
223	82	88	80	79	88	75	78	79	79	80
224	79	82	82	82	82	79	79	88	88	82
225	88	79	79	79	79	88	82	75	75	79
226	75	88	82	88	88	75	79	80	82	88
227	80	75	79	82	76	75	88	78	80	79
228	88	82	88	75	82	75	79	80	80	89
229	75	79	75	75	79	88	85	88	86	83
230	75	88	82	88	88	75	79	80	82	88
231	80	75	79	82	76	75	88	78	80	79
232	82	88	80	79	88	75	78	79	79	80
233	80	82	70	82	90	82	90	79	80	77
234	82	79	82	79	80	79	80	80	82	83
235	75	79	75	75	79	88	85	88	86	83
236	75	88	82	88	88	75	79	80	82	88
237	79	82	82	82	82	79	79	88	88	82
238	88	79	79	79	79	88	82	75	75	79

239	75	88	82	88	88	75	79	80	82	88
240	80	75	79	82	76	75	88	78	80	79
241	88	82	88	75	82	75	79	80	80	89
242	75	79	75	75	79	88	85	88	86	83
243	75	88	82	88	88	75	79	80	82	88
244	80	75	79	82	76	75	88	78	80	79
245	82	88	80	79	88	75	78	79	79	80
246	80	82	70	82	90	82	90	79	80	77
247	82	79	82	79	80	79	80	80	82	83
248	79	88	79	88	80	88	82	84	79	80
249	82	88	80	79	88	75	78	79	79	80
250	79	82	82	82	82	79	79	88	88	82
251	88	79	79	79	79	88	82	75	75	79
252	75	88	82	88	88	75	79	80	82	88
253	80	75	79	82	76	75	88	78	80	79
254	88	82	88	75	82	75	79	80	80	89
255	75	79	75	75	79	88	85	88	86	83
256	75	88	82	88	88	75	79	80	82	88
257	80	75	79	82	76	75	88	78	80	79
258	82	88	80	79	88	75	78	79	79	80
259	80	82	70	82	90	82	90	79	80	77
260	82	79	82	79	80	79	80	80	82	83
261	75	88	82	88	88	75	79	80	82	88
262	80	75	79	82	76	75	88	78	80	79
263	88	82	88	75	82	75	79	80	80	89
264	75	79	75	75	79	88	85	88	86	83
265	75	88	82	88	88	75	79	80	82	88
266	80	75	79	82	76	75	88	78	80	79

267	82	88	80	79	88	75	78	79	79	80
268	82	88	80	79	88	75	78	79	79	80
269	79	82	82	82	82	79	79	88	88	82
270	88	79	79	79	79	88	82	75	75	79
271	75	88	82	88	88	75	79	80	82	88
272	80	75	79	82	76	75	88	78	80	79
273	88	82	88	75	82	75	79	80	80	89
274	75	79	75	75	79	88	85	88	86	83
275	75	88	82	88	88	75	79	80	82	88
276	80	75	79	82	76	75	88	78	80	79
277	82	88	80	79	88	75	78	79	79	80
278	80	82	70	82	90	82	90	79	80	77
279	82	79	82	79	80	79	80	80	82	83
280	75	79	75	75	79	88	85	88	86	83
281	75	88	82	88	88	75	79	80	82	88
282	80	75	79	82	76	75	88	78	80	79
283	82	88	80	79	88	75	78	79	79	80
284	80	82	70	82	90	82	90	79	80	77
285	82	79	82	79	80	79	80	80	82	83
286	75	88	82	88	88	75	79	80	82	88
287	80	75	79	82	76	75	88	78	80	79
288	88	82	88	75	82	75	79	80	80	89
289	75	79	75	75	79	88	85	88	86	83
290	75	88	82	88	88	75	79	80	82	88
291	80	75	79	82	76	75	88	78	80	79
292	82	88	80	79	88	75	78	79	79	80
293	80	82	70	82	90	82	90	79	80	77
294	82	79	82	79	80	79	80	80	82	83

295	75	79	75	75	79	88	85	88	86	83
296	75	88	82	88	88	75	79	80	82	88
297	80	75	79	82	76	75	88	78	80	79
298	82	88	80	79	88	75	78	79	79	80
299	80	82	70	82	90	82	90	79	80	77
300	82	79	82	79	80	79	80	80	82	83

Appendix D: Result for 200 Patients from Proposed Approach

Health Status for all Patients								
Patient ID	Sugar Before Meals	SBM Condition	Sugar After Meals	SAM Condition	High BP	High BP Condition	Low BP	Low BP Condition
101	82.8506011962891	NORMAL	172.688598632813	Hyperglycaemia	139.748001098633	Normal	80.8542022705078	Normal
102	106.807403564453	NORMAL	185.66520690918	Hyperglycaemia	133.758804321289	Normal	79.8560028076172	Hypotension
103	90.8361968994141	NORMAL	200.638198852539	Hyperglycaemia	137.751602172852	Normal	81.8524017333984	Normal
104	93.8308029174805	NORMAL	162.706604003906	Hyperglycaemia	130.764205932617	Normal	80.8542022705078	Normal
105	91.8343963623047	NORMAL	171.690399169922	Hyperglycaemia	137.751602172852	Normal	80.8542022705078	Normal
106	94.8290023803711	NORMAL	167.697601318359	Hyperglycaemia	132.760604858398	Normal	79.8560028076172	Hypotension
107	91.8343963623047	NORMAL	165.701202392578	Hyperglycaemia	141.744400024414	Hypertension	81.8524017333984	Normal
108	82.8506011962891	NORMAL	158.713806152344	Hyperglycaemia	134.75700378418	Normal	79.8560028076172	Hypotension
109	80.8542022705078	Hypoglycaemia	158.713806152344	Hyperglycaemia	137.751602172852	Normal	81.8524017333984	Normal
110	90.8361968994141	NORMAL	207.625595092773	Hyperglycaemia	131.762405395508	Normal	78.8578033447266	Hypotension
111	94.8290023803711	NORMAL	145.737197875977	Hyperglycaemia	130.764205932617	Normal	80.8542022705078	Normal
112	134.75700378418	Hyperglycaemia	209.621994018555	Hyperglycaemia	137.751602172852	Normal	80.8542022705078	Normal
113	89.8379974365234	NORMAL	193.650802612305	Hyperglycaemia	137.751602172852	Normal	81.8524017333984	Normal
114	105.809196472168	NORMAL	164.703002929688	Hyperglycaemia	131.762405395508	Normal	78.8578033447266	Hypotension
115	204.630996704102	Hyperglycaemia	296.465393066406	Hyperglycaemia	132.760604858398	Normal	79.8560028076172	Hypotension
116	117.78759765625	Hyperglycaemia	209.621994018555	Hyperglycaemia	139.748001098633	Normal	80.8542022705078	Normal
117	117.78759765625	Hyperglycaemia	211.618392944336	Hyperglycaemia	133.758804321289	Normal	79.8560028076172	Hypotension
118	87.8415985107422	NORMAL	158.713806152344	Hyperglycaemia	137.751602172852	Normal	81.8524017333984	Normal
119	81.8524017333984	Hypoglycaemia	159.712005615234	Hyperglycaemia	137.751602172852	Normal	79.8560028076172	Hypotension
120	91.8343963623047	NORMAL	189.658004760742	Hyperglycaemia	130.764205932617	Normal	81.8524017333984	Normal
121	104.810997009277	NORMAL	172.688598632813	Hyperglycaemia	139.748001098633	Normal	79.8560028076172	Hypotension
122	102.814598083496	NORMAL	187.661605834961	Hyperglycaemia	137.751602172852	Normal	81.8524017333984	Normal
123	92.8326034545898	NORMAL	205.629196166992	Hyperglycaemia	137.751602172852	Normal	78.8578033447266	Hypotension
124	92.8326034545898	NORMAL	162.706604003906	Hyperglycaemia	133.758804321289	Normal	80.8542022705078	Normal
125	123.776802062988	Hyperglycaemia	195.647201538086	Hyperglycaemia	131.762405395508	Normal	80.8542022705078	Normal
126	104.810997009277	NORMAL	242.562606811523	Hyperglycaemia	142.742599487305	Hypertension	81.8524017333984	Normal
127	127.769599914551	Hyperglycaemia	292.472595214844	Hyperglycaemia	136.753402709961	Normal	78.8578033447266	Hypotension
128	105.809196472168	NORMAL	248.551803588867	Hyperglycaemia	137.751602172852	Normal	79.8560028076172	Hypotension
129	115.791198730469	Hyperglycaemia	243.560806274414	Hyperglycaemia	132.760604858398	Normal	80.8542022705078	Normal
130	125.77320098877	Hyperglycaemia	290.476196289063	Hyperglycaemia	139.748001098633	Normal	79.8560028076172	Hypotension
131	112.796600341797	Hyperglycaemia	245.557205200195	Hyperglycaemia	134.75700378418	Normal	81.8524017333984	Normal
132	106.807403564453	NORMAL	244.559005737305	Hyperglycaemia	140.746200561523	Hypertension	78.8578033447266	Hypotension
134	109.802001953125	NORMAL	242.562606811523	Hyperglycaemia	135.75520324707	Normal	80.8542022705078	Normal
135	107.805603027344	NORMAL	245.557205200195	Hyperglycaemia	137.751602172852	Normal	81.8524017333984	Normal
136	121.780403137207	Hyperglycaemia	286.4833984375	Hyperglycaemia	136.753402709961	Normal	78.8578033447266	Hypotension
137	106.807403564453	NORMAL	239.567993164063	Hyperglycaemia	136.753402709961	Normal	79.8560028076172	Hypotension
138	108.803802490234	NORMAL	246.555404663086	Hyperglycaemia	133.758804321289	Normal	79.8560028076172	Hypotension
139	119.783996582031	Hyperglycaemia	284.486999511719	Hyperglycaemia	145.737197875977	Hypertension	81.8524017333984	Normal
140	103.812797546387	NORMAL	236.573394775391	Hyperglycaemia	135.75520324707	Normal	79.8560028076172	Hypotension
141	109.802001953125	NORMAL	247.553604125977	Hyperglycaemia	139.748001098633	Normal	81.8524017333984	Normal

142	117.78759765625	Hyperglycaemia	282.490600585938	Hyperglycaemia	140.746200561523	Hypertension	78.8578033447266	Hypotension
143	100.818199157715	NORMAL	233.578796386719	Hyperglycaemia	131.762405395508	Normal	80.8542022705078	Normal
144	110.800201416016	Hyperglycaemia	248.551803588867	Hyperglycaemia	140.746200561523	Hypertension	80.8542022705078	Normal
145	110.800201416016	Hyperglycaemia	282.490600585938	Hyperglycaemia	135.75520324707	Normal	81.8524017333984	Normal
146	97.823600769043	NORMAL	230.584197998047	Hyperglycaemia	131.762405395508	Normal	78.8578033447266	Hypotension
147	111.798400878906	Hyperglycaemia	249.550003051758	Hyperglycaemia	137.751602172852	Normal	79.8560028076172	Hypotension
148	108.803802490234	NORMAL	279.496002197266	Hyperglycaemia	131.762405395508	Normal	80.8542022705078	Normal
149	94.8290023803711	NORMAL	227.589599609375	Hyperglycaemia	141.744400024414	Hypertension	79.8560028076172	Hypotension
150	112.796600341797	Hyperglycaemia	250.548202514648	Hyperglycaemia	132.760604858398	Normal	80.8542022705078	Normal
151	106.807403564453	NORMAL	277.499603271484	Hyperglycaemia	139.748001098633	Normal	81.8524017333984	Normal
152	91.8343963623047	NORMAL	224.595001220703	Hyperglycaemia	132.760604858398	Normal	81.8524017333984	Normal
153	113.794799804688	Hyperglycaemia	251.546401977539	Hyperglycaemia	140.746200561523	Hypertension	79.8560028076172	Hypotension
154	104.810997009277	NORMAL	275.503173828125	Hyperglycaemia	134.75700378418	Normal	81.8524017333984	Normal
155	88.8397979736328	NORMAL	221.600402832031	Hyperglycaemia	128.767807006836	Normal	78.8578033447266	Hypotension
156	114.792999267578	Hyperglycaemia	252.54460144043	Hyperglycaemia	140.746200561523	Hypertension	80.8542022705078	Normal
157	102.814598083496	NORMAL	273.506805419922	Hyperglycaemia	138.749801635742	Normal	80.8542022705078	Normal
158	85.8451995849609	NORMAL	218.605804443359	Hyperglycaemia	136.753402709961	Normal	81.8524017333984	Normal
159	115.791198730469	Hyperglycaemia	253.54280090332	Hyperglycaemia	133.758804321289	Normal	78.8578033447266	Hypotension
160	100.818199157715	NORMAL	271.510406494141	Hyperglycaemia	145.737197875977	Hypertension	79.8560028076172	Hypotension
161	95.8272018432617	NORMAL	216.609405517578	Hyperglycaemia	137.751602172852	Normal	80.8542022705078	Normal
162	116.789398193359	Hyperglycaemia	254.541000366211	Hyperglycaemia	132.760604858398	Normal	79.8560028076172	Hypotension
163	98.8218002319336	NORMAL	269.514007568359	Hyperglycaemia	141.744400024414	Hypertension	81.8524017333984	Normal
164	93.8308029174805	NORMAL	214.613006591797	Hyperglycaemia	134.75700378418	Normal	79.8560028076172	Hypotension
165	117.78759765625	Hyperglycaemia	255.539199829102	Hyperglycaemia	137.751602172852	Normal	81.8524017333984	Normal
166	96.8253936767578	NORMAL	267.517578125	Hyperglycaemia	131.762405395508	Normal	79.8560028076172	Hypotension
167	91.8343963623047	NORMAL	212.616592407227	Hyperglycaemia	130.764205932617	Normal	81.8524017333984	Normal
168	118.785797119141	Hyperglycaemia	256.537414550781	Hyperglycaemia	137.751602172852	Normal	78.8578033447266	Hypotension
169	94.8290023803711	NORMAL	265.521209716797	Hyperglycaemia	137.751602172852	Normal	80.8542022705078	Normal
170	89.8379974365234	NORMAL	210.620193481445	Hyperglycaemia	131.762405395508	Normal	80.8542022705078	Normal
171	119.783996582031	Hyperglycaemia	257.535614013672	Hyperglycaemia	132.760604858398	Normal	81.8524017333984	Normal
172	92.8326034545898	NORMAL	263.524810791016	Hyperglycaemia	139.748001098633	Normal	78.8578033447266	Hypotension
173	87.8415985107422	NORMAL	208.623794555664	Hyperglycaemia	133.758804321289	Normal	79.8560028076172	Hypotension
174	120.782203674316	Hyperglycaemia	258.533813476563	Hyperglycaemia	137.751602172852	Normal	80.8542022705078	Normal
175	90.8361968994141	NORMAL	261.528411865234	Hyperglycaemia	137.751602172852	Normal	79.8560028076172	Hypotension
176	85.8451995849609	NORMAL	206.627395629883	Hyperglycaemia	130.764205932617	Normal	81.8524017333984	Normal
177	121.780403137207	Hyperglycaemia	259.532012939453	Hyperglycaemia	139.748001098633	Normal	78.8578033447266	Hypotension
178	88.8397979736328	NORMAL	259.532012939453	Hyperglycaemia	137.751602172852	Normal	80.8542022705078	Normal
179	84.8470001220703	NORMAL	204.630996704102	Hyperglycaemia	137.751602172852	Normal	80.8542022705078	Normal
180	122.778602600098	Hyperglycaemia	260.530212402344	Hyperglycaemia	133.758804321289	Normal	81.8524017333984	Normal
181	86.8433990478516	NORMAL	257.535614013672	Hyperglycaemia	131.762405395508	Normal	78.8578033447266	Hypotension
182	81.8524017333984	Hypoglycaemia	202.63459777832	Hyperglycaemia	142.742599487305	Hypertension	79.8560028076172	Hypotension
183	123.776802062988	Hyperglycaemia	261.528411865234	Hyperglycaemia	136.753402709961	Normal	79.8560028076172	Hypotension

184	84.8470001220703	NORMAL	255.539199829102	Hyperglycaemia	137.751602172852	Normal	81.8524017333984	Normal
185	79.8560028076172	Hypoglycaemia	200.638198852539	Hyperglycaemia	132.760604858398	Normal	79.8560028076172	Hypotension
186	124.775001525879	Hyperglycaemia	262.526611328125	Hyperglycaemia	139.748001098633	Normal	81.8524017333984	Normal
187	82.8506011962891	NORMAL	253.54280090332	Hyperglycaemia	134.75700378418	Normal	78.8578033447266	Hypotension
188	77.8595962524414	Hypoglycaemia	198.641799926758	Hyperglycaemia	140.746200561523	Hypertension	80.8542022705078	Normal
189	125.77320098877	Hyperglycaemia	263.524810791016	Hyperglycaemia	132.760604858398	Normal	80.8542022705078	Normal
190	80.8542022705078	Hypoglycaemia	251.546401977539	Hyperglycaemia	135.75520324707	Normal	81.8524017333984	Normal
191	75.8631973266602	Hypoglycaemia	196.645401000977	Hyperglycaemia	137.751602172852	Normal	78.8578033447266	Hypotension
192	126.77140045166	Hyperglycaemia	264.523010253906	Hyperglycaemia	136.753402709961	Normal	79.8560028076172	Hypotension
193	78.8578033447266	Hypoglycaemia	249.550003051758	Hyperglycaemia	136.753402709961	Normal	80.8542022705078	Normal
194	73.8667984008789	Hypoglycaemia	194.649002075195	Hyperglycaemia	133.758804321289	Normal	79.8560028076172	Hypotension
195	127.769599914551	Hyperglycaemia	265.521209716797	Hyperglycaemia	145.737197875977	Hypertension	80.8542022705078	Normal
196	76.8613967895508	Hypoglycaemia	247.553604125977	Hyperglycaemia	135.75520324707	Normal	81.8524017333984	Normal
197	71.8703994750977	Hypoglycaemia	192.652603149414	Hyperglycaemia	139.748001098633	Normal	78.8578033447266	Hypotension
198	128.767807006836	Hyperglycaemia	266.519409179688	Hyperglycaemia	140.746200561523	Hypertension	79.8560028076172	Hypotension
199	74.8649978637695	Hypoglycaemia	245.557205200195	Hyperglycaemia	131.762405395508	Normal	80.8542022705078	Normal
200	69.8740005493164	Hypoglycaemia	190.656204223633	Hyperglycaemia	140.746200561523	Hypertension	79.8560028076172	Hypotension
201	105.809196472168	NORMAL	251.546401977539	Hyperglycaemia	135.75520324707	Normal	81.8524017333984	Normal
202	131.762405395508	Hyperglycaemia	248.551803588867	Hyperglycaemia	131.762405395508	Normal	78.8578033447266	Hypotension
203	127.769599914551	Hyperglycaemia	254.541000366211	Hyperglycaemia	137.751602172852	Normal	80.8542022705078	Normal
204	145.737197875977	Hyperglycaemia	265.521209716797	Hyperglycaemia	131.762405395508	Normal	80.8542022705078	Normal
205	106.807403564453	NORMAL	252.54460144043	Hyperglycaemia	141.744400024414	Hypertension	81.8524017333984	Normal
206	129.766006469727	Hyperglycaemia	246.555404663086	Hyperglycaemia	132.760604858398	Normal	78.8578033447266	Hypotension
207	124.775001525879	Hyperglycaemia	251.546401977539	Hyperglycaemia	139.748001098633	Normal	79.8560028076172	Hypotension
208	144.738998413086	Hyperglycaemia	263.524810791016	Hyperglycaemia	132.760604858398	Normal	80.8542022705078	Normal
209	107.805603027344	NORMAL	253.54280090332	Hyperglycaemia	140.746200561523	Hypertension	79.8560028076172	Hypotension
210	127.769599914551	Hyperglycaemia	244.559005737305	Hyperglycaemia	140.746200561523	Hypertension	79.8560028076172	Hypotension
211	121.780403137207	Hyperglycaemia	248.551803588867	Hyperglycaemia	134.75700378418	Normal	80.8542022705078	Normal
212	143.740798950195	Hyperglycaemia	261.528411865234	Hyperglycaemia	140.746200561523	Hypertension	78.8578033447266	Hypotension
213	108.803802490234	NORMAL	254.541000366211	Hyperglycaemia	138.749801635742	Normal	79.8560028076172	Hypotension
214	125.77320098877	Hyperglycaemia	242.562606811523	Hyperglycaemia	133.758804321289	Normal	80.8542022705078	Normal
215	118.785797119141	Hyperglycaemia	245.557205200195	Hyperglycaemia	137.751602172852	Normal	79.8560028076172	Hypotension
216	142.742599487305	Hyperglycaemia	259.532012939453	Hyperglycaemia	137.751602172852	Normal	81.8524017333984	Normal
217	109.802001953125	NORMAL	255.539199829102	Hyperglycaemia	130.764205932617	Normal	78.8578033447266	Hypotension
218	123.776802062988	Hyperglycaemia	240.566192626953	Hyperglycaemia	139.748001098633	Normal	80.8542022705078	Normal
219	115.791198730469	Hyperglycaemia	242.562606811523	Hyperglycaemia	137.751602172852	Normal	80.8542022705078	Normal
220	141.744400024414	Hyperglycaemia	257.535614013672	Hyperglycaemia	137.751602172852	Normal	81.8524017333984	Normal
221	110.800201416016	Hyperglycaemia	256.537414550781	Hyperglycaemia	133.758804321289	Normal	78.8578033447266	Hypotension
222	121.780403137207	Hyperglycaemia	238.569793701172	Hyperglycaemia	131.762405395508	Normal	79.8560028076172	Hypotension
223	112.796600341797	Hyperglycaemia	239.567993164063	Hyperglycaemia	142.742599487305	Hypertension	79.8560028076172	Hypotension
224	140.746185302734	Hyperglycaemia	255.539184570313	Hyperglycaemia	136.753402709961	Normal	81.8524017333984	Normal
225	111.798400878906	Hyperglycaemia	257.535614013672	Hyperglycaemia	137.751602172852	Normal	79.8560028076172	Hypotension

226	110.800201416016	Hyperglycaemia	236.573394775391	Hyperglycaemia	132.760604858398	Normal	81.8524017333984	Normal
227	109.802001953125	NORMAL	236.573394775391	Hyperglycaemia	139.748001098633	Normal	78.8578033447266	Hypotension
228	139.748001098633	Hyperglycaemia	253.54280090332	Hyperglycaemia	134.75700378418	Normal	80.8542022705078	Normal
229	112.796600341797	Hyperglycaemia	258.533813476563	Hyperglycaemia	140.746200561523	Hypertension	80.8542022705078	Normal
230	108.803802490234	NORMAL	234.576995849609	Hyperglycaemia	132.760604858398	Normal	81.8524017333984	Normal
231	106.807403564453	NORMAL	233.578796386719	Hyperglycaemia	135.75520324707	Normal	78.8578033447266	Hypotension
232	138.749801635742	Hyperglycaemia	251.546401977539	Hyperglycaemia	137.751602172852	Normal	79.8560028076172	Hypotension
233	113.794799804688	Hyperglycaemia	259.532012939453	Hyperglycaemia	136.753402709961	Normal	80.8542022705078	Normal
234	106.807403564453	NORMAL	232.580596923828	Hyperglycaemia	136.753402709961	Normal	79.8560028076172	Hypotension
235	103.812797546387	NORMAL	230.584197998047	Hyperglycaemia	133.758804321289	Normal	80.8542022705078	Normal
236	137.751602172852	Hyperglycaemia	249.550003051758	Hyperglycaemia	145.737197875977	Hypertension	81.8524017333984	Normal
237	114.792999267578	Hyperglycaemia	260.530212402344	Hyperglycaemia	135.75520324707	Normal	81.8524017333984	Normal
238	104.810997009277	NORMAL	230.584197998047	Hyperglycaemia	139.748001098633	Normal	79.8560028076172	Hypotension
239	100.818199157715	NORMAL	227.589599609375	Hyperglycaemia	140.746185302734	Hypertension	81.8523941040039	Normal
240	136.753402709961	Hyperglycaemia	247.553604125977	Hyperglycaemia	131.762405395508	Normal	78.8578033447266	Hypotension
241	115.791198730469	Hyperglycaemia	261.528411865234	Hyperglycaemia	137.751602172852	Normal	80.8542022705078	Normal
242	102.814598083496	NORMAL	228.587799072266	Hyperglycaemia	132.760604858398	Normal	80.8542022705078	Normal
243	97.823600769043	NORMAL	224.595001220703	Hyperglycaemia	141.744400024414	Hypertension	81.8524017333984	Normal
244	135.75520324707	Hyperglycaemia	245.557205200195	Hyperglycaemia	134.75700378418	Normal	78.8578033447266	Hypotension
245	116.789398193359	Hyperglycaemia	262.526611328125	Hyperglycaemia	137.751602172852	Normal	79.8560028076172	Hypotension
246	100.818199157715	NORMAL	226.591400146484	Hyperglycaemia	131.762405395508	Normal	80.8542022705078	Normal
247	95.8272018432617	NORMAL	222.598602294922	Hyperglycaemia	137.751602172852	Normal	79.8560028076172	Hypotension
248	134.75700378418	Hyperglycaemia	243.560806274414	Hyperglycaemia	137.751602172852	Normal	81.8524017333984	Normal
249	117.78759765625	Hyperglycaemia	263.524810791016	Hyperglycaemia	132.760604858398	Normal	79.8560028076172	Hypotension
250	98.8218002319336	NORMAL	224.595001220703	Hyperglycaemia	141.744400024414	Hypertension	81.8524017333984	Normal
251	93.8308029174805	NORMAL	220.602203369141	Hyperglycaemia	134.75700378418	Normal	79.8560028076172	Hypotension
252	133.758804321289	Hyperglycaemia	241.564407348633	Hyperglycaemia	137.751602172852	Normal	81.8524017333984	Normal
253	118.785797119141	Hyperglycaemia	264.523010253906	Hyperglycaemia	131.762405395508	Normal	78.8578033447266	Hypotension
254	96.8254013061523	NORMAL	222.598602294922	Hyperglycaemia	130.764205932617	Normal	80.8542022705078	Normal
255	91.8343963623047	NORMAL	218.605804443359	Hyperglycaemia	137.751602172852	Normal	80.8542022705078	Normal
256	132.760604858398	Hyperglycaemia	239.567993164063	Hyperglycaemia	137.751602172852	Normal	81.8524017333984	Normal
257	119.783996582031	Hyperglycaemia	265.521209716797	Hyperglycaemia	131.762405395508	Normal	78.8578033447266	Hypotension
258	94.8290023803711	NORMAL	220.602203369141	Hyperglycaemia	132.760604858398	Normal	79.8560028076172	Hypotension
259	89.8379974365234	NORMAL	216.609405517578	Hyperglycaemia	139.748001098633	Normal	80.8542022705078	Normal
260	131.762405395508	Hyperglycaemia	237.571594238281	Hyperglycaemia	133.758804321289	Normal	79.8560028076172	Hypotension
261	120.782203674316	Hyperglycaemia	266.519409179688	Hyperglycaemia	137.751602172852	Normal	81.8524017333984	Normal
262	92.8326034545898	NORMAL	218.605804443359	Hyperglycaemia	137.751602172852	Normal	78.8578033447266	Hypotension
263	87.8415985107422	NORMAL	214.613006591797	Hyperglycaemia	130.764205932617	Normal	80.8542022705078	Normal
264	130.764205932617	Hyperglycaemia	235.5751953125	Hyperglycaemia	139.748001098633	Normal	80.8542022705078	Normal
265	121.780403137207	Hyperglycaemia	267.517608642578	Hyperglycaemia	137.751602172852	Normal	81.8524017333984	Normal
266	90.8361968994141	NORMAL	216.609405517578	Hyperglycaemia	137.751602172852	Normal	78.8578033447266	Hypotension
267	85.8451995849609	NORMAL	212.616592407227	Hyperglycaemia	133.758804321289	Normal	79.8560028076172	Hypotension

268	129.766006469727	Hyperglycaemia	233.578796386719	Hyperglycaemia	131.762405395508	Normal	79.8560028076172	Hypotension
269	122.778602600098	Hyperglycaemia	268.515808105469	Hyperglycaemia	142.742599487305	Hypertension	81.8524017333984	Normal
270	88.8397979736328	NORMAL	214.613006591797	Hyperglycaemia	136.753402709961	Normal	79.8560028076172	Hypotension
271	83.8488006591797	NORMAL	210.620193481445	Hyperglycaemia	137.751602172852	Normal	81.8524017333984	Normal
272	128.767807006836	Hyperglycaemia	231.582397460938	Hyperglycaemia	132.760604858398	Normal	78.8578033447266	Hypotension
273	123.776802062988	Hyperglycaemia	269.514007568359	Hyperglycaemia	139.748001098633	Normal	80.8542022705078	Normal
274	86.8433990478516	NORMAL	212.616592407227	Hyperglycaemia	134.75700378418	Normal	80.8542022705078	Normal
275	81.8524017333984	Hypoglycaemia	208.623794555664	Hyperglycaemia	140.746200561523	Hypertension	81.8524017333984	Normal
276	127.769599914551	Hyperglycaemia	229.585998535156	Hyperglycaemia	132.760604858398	Normal	78.8578033447266	Hypotension
277	124.775001525879	Hyperglycaemia	270.51220703125	Hyperglycaemia	135.75520324707	Normal	79.8560028076172	Hypotension
278	84.8470001220703	NORMAL	210.620193481445	Hyperglycaemia	137.751602172852	Normal	80.8542022705078	Normal
279	79.8560028076172	Hypoglycaemia	206.627395629883	Hyperglycaemia	136.753402709961	Normal	79.8560028076172	Hypotension
280	126.77140045166	Hyperglycaemia	227.589599609375	Hyperglycaemia	136.753402709961	Normal	80.8542022705078	Normal
281	125.77320098877	Hyperglycaemia	271.510406494141	Hyperglycaemia	133.758804321289	Normal	81.8524017333984	Normal
282	82.8506011962891	NORMAL	208.623794555664	Hyperglycaemia	145.737197875977	Hypertension	78.8578033447266	Hypotension
283	77.8595962524414	Hypoglycaemia	204.630996704102	Hyperglycaemia	135.75520324707	Normal	79.8560028076172	Hypotension
284	125.77320098877	Hyperglycaemia	225.593200683594	Hyperglycaemia	139.748001098633	Normal	80.8542022705078	Normal
285	126.77140045166	Hyperglycaemia	272.508605957031	Hyperglycaemia	140.746200561523	Hypertension	79.8560028076172	Hypotension
286	80.8542022705078	Hypoglycaemia	206.627395629883	Hyperglycaemia	131.762405395508	Normal	81.8524017333984	Normal
287	75.8631973266602	Hypoglycaemia	202.63459777832	Hyperglycaemia	140.746200561523	Hypertension	78.8578033447266	Hypotension
288	124.775001525879	Hyperglycaemia	223.596801757813	Hyperglycaemia	135.75520324707	Normal	80.8542022705078	Normal
289	127.769599914551	Hyperglycaemia	273.506805419922	Hyperglycaemia	131.762405395508	Normal	80.8542022705078	Normal
290	78.8578033447266	Hypoglycaemia	204.630996704102	Hyperglycaemia	137.751602172852	Normal	81.8524017333984	Normal
291	73.8667984008789	Hypoglycaemia	200.638198852539	Hyperglycaemia	131.762405395508	Normal	78.8578033447266	Hypotension
292	123.776802062988	Hyperglycaemia	221.600402832031	Hyperglycaemia	141.744400024414	Hypertension	79.8560028076172	Hypotension
293	128.767807006836	Hyperglycaemia	274.505004882813	Hyperglycaemia	132.760604858398	Normal	80.8542022705078	Normal
294	76.8613967895508	Hypoglycaemia	202.63459777832	Hyperglycaemia	139.748001098633	Normal	79.8560028076172	Hypotension
295	71.8703994750977	Hypoglycaemia	198.641799926758	Hyperglycaemia	132.760604858398	Normal	80.8542022705078	Normal
296	122.778602600098	Hyperglycaemia	219.60400390625	Hyperglycaemia	140.746200561523	Hypertension	81.8524017333984	Normal
297	129.766006469727	Hyperglycaemia	275.503204345703	Hyperglycaemia	134.75700378418	Normal	78.8578033447266	Hypotension
298	74.8649978637695	Hypoglycaemia	200.638198852539	Hyperglycaemia	128.767807006836	Normal	79.8560028076172	Hypotension
299	160.710205078125	Hyperglycaemia	466.159393310547	Unknown Parameter	140.746200561523	Hypertension	80.8542022705078	Normal
300	121.780403137207	Hyperglycaemia	217.607604980469	Hyperglycaemia	138.749801635742	Normal	79.8560028076172	Hypotension

Appendix E: Source Code

E.1. Checker Code

The source code for different classes of proposed approach is given here as follows.

```
<%@page import="java.sql.*,java.io.*"%>
<%@page import="java.lang.*"%>
    <html>
    <head>
    <title>Checking Sugar and BP Levels in Human Body</title>
    </head>
<style>
.home{
            position: absolute;
            padding-right:20px;
            margin-top:-15px;
            margin-left:10px;

  }
</style>
<body>


<img src="images/header.jpg" alt="Header" width="100%" height="120"><br />
<a class="home" href="index.jsp"><h4>HOME</h4></a>
<%
double beforem=0,afterm=0,highbp=0,lowbp=0;
int p=0,ppid=0;
Connection con=null;
Statement st=null;
ResultSet rs=null;
PreparedStatement pstmt=null;

try{
       Class.forName("com.mysql.jdbc.Driver");
       con = DriverManager.getConnection("jdbc:mysql://localhost:3306/Sugur", "root", "root");
       st=con.createStatement();
                    rs=st.executeQuery("select * from checker where sno=1");
if(rs.next()){
ppid=rs.getInt("pid");
beforem=rs.getDouble("beforem");
afterm=rs.getDouble("afterm");
highbp=rs.getDouble("highbp");
lowbp=rs.getDouble("lowbp");
}
/******************** Sugar Triggering **********************/
%>
<center>
<p><font size="+2" color="#0099FF" ><b>Health Status for Patient</b> -<%=ppid%></font></p>
<table border="1" bgcolor="" width="730" height="250" style="margin-left:4">
  <th><font color="#0033FF">Sugar Level Before Meals</th>
```

```
  <th><font color="#0033FF">Sugar Level After Meals</th>
<tr>

<%
/************ Unknown Parameter  for Before meals**************/
if(beforem<60 || beforem>400)
{%>
<td width="100"> Condition :      <font color="#FF0000"><b>Unknown
Parameter</b></font><br />
<%out.println("Sugar Level: "+beforem);%>
<br />(The patient glucose levels are found to be abnormal than normal glucose levels and Risk is not defined. Please
contact your doctor as soon as possible.)
<br /><br /><font color="#FF6600"><strong>Recommendations</strong></font>
<br /><br /><font color="#FF0000"> Patient needs to contact doctor as soon as possible</font>
<br />
<br /></td>
<%
/******************* Trigger Coding ***************************/
try{
Statement st1=con.createStatement();
st.executeUpdate("insert into doctor(pid,level) values('"+ppid+"','"+beforem+"')");
}catch(Exception e2){}
}
/**************** Hypoglycaemia for before meals***************/
if(beforem>=60 && beforem<82)
{%>
<td width="100"> Condition :      <font color="#FF0000"><b>Hypoglycaemia</b></font><br
/>
<%out.println("Sugar Level: "+beforem);%>
<br />(The patient glucose levels are found to be less than normal values and Risk is identified as Hypoglycemia.)
<br /><br /><font color="#FF6600"><strong>Recommendations</strong></font>
<br />1. Patient needs to take some sugar contents or sublets
<br />2. Please eat food in time and also maintain proper diet
<br /><br />
</td>
<%
}
/****************** Normal for Before meals********************/
if(beforem>=82 && beforem<=110)
{%>
<td width="100">Condition :      <font color="#006600"><b>Normal</b></font><br />
<%out.println("Sugar Level: "+beforem);%>
<br />(The patient glucose levels are found to be normal and No Risk is identified.)<br />
<br /><br /><font color="#FF6600"><strong>Recommendations</strong></font>
<br />1. Please maintain good food habits
<br />2. please eat food in time and also maintain proper diet
<br />3. Keep doing exercise
</td>
<%
}
/********************** Hyperglycaemia  for Before meals*******/
if(beforem>110 && beforem<=400)
{%>
```

```
<td width="100"> Condition :      <font color="#FF0000"><b>Hyperglycaemia</b></font><br
/>
<%out.println("Sugar Level: "+beforem);%>
<br />(The patient glucose levels are found to be very high than normal glucose levels and Risk is identified as
Hyperglycemia.)
<br /><br /><font color="#FF6600"><strong>Recommendations</strong></font>
<br />1. Patient needs to reduce the sugar contents in the diet
<br />2. Please eat limited food in time and also maintain proper diet to control the glucose levels
<br />3.  also keep doing excercise daily
</td>
<%
}

/***************** Unknown Parameter  for After meals**********/
if(afterm<60 || afterm>400)
{%>
<td width="100"> Condition :      <font color="#FF0000"><b>Unknown
Parameter</b></font><br />
<%out.println("Sugar Level: "+afterm);%>
<br />(The patient glucose levels are found to be abnormal than normal glucose levels and Risk is not defined. Please
contact your doctor as soon as possible.)
<br /><br /><font color="#FF6600"><strong>Recommendations</strong></font>
<br /><br /><font color="#FF0000"> Patient needs to contact doctor as soon as possible</font>
<br />
<br />
</td>
<%
/******************** Trigger Coding *************************/
try{
Statement st2=con.createStatement();
st.executeUpdate("insert into doctor(pid,level) values('"+ppid+"','"+afterm+"')");
}catch(Exception e2){}
}
/************** Hypoglycaemia for after meals******************/
if(afterm>=60 && afterm<82)
{%>
<td width="100"> Condition :      <font color="#FF0000"><b>Hypoglycaemia</b></font><br
/>
<%out.println("Sugar Level: "+afterm);%>
<br />(The patient glucose levels are found to be less than normal values and Risk is identified as Hypoglycemia.)
<br /><br /><font color="#FF6600"><strong>Recommendations</strong></font>
<br />1. Patient needs to take some sugar contents or sublets
<br />2. Please eat food in time and also maintain proper diet
<br /><br />
</td>
<%
}
/************ Normal for after meals***************************/
if(afterm>=82 && afterm<=140)
{%>
<td width="100">Condition :      <font color="#006600"><b>Normal</b></font><br />
<%out.println("Sugar Level: "+afterm);%>
<br />(The patient glucose levels are found to be normal and No Risk is identified.)
```

```
<br /><br /><font color="#FF6600"><strong>Recommendations</strong></font>
<br />1. Please maintain good food habits
<br />2. please eat food in time and also maintain proper diet
<br />3. Keep doing exercise
</td>
<%
}
/********** Hyperglycaemia  for after meals********************/
if(afterm>140 && afterm<=400)
{%>
<td width="100"> Condition :      <font color="#FF0000"><b>Hyperglycaemia</b></font><br
/>
<%out.println("Sugar Level: "+afterm);%>
<br />(The patient glucose levels are found to be very high than normal glucose levels and Risk is identified as
Hyperglycemia.)
<br /><br /><font color="#FF6600"><strong>Recommendations</strong></font>
<br />1. Patient needs to reduce the sugar contents in the diet
<br />2. Please eat limited food in time and also maintain proper diet to control the glucose levels
<br />3. also keep doing excercise daily
</td>
<%
}
%></tr><tr>
  <td align="center"><font color="#0033FF"><b> Low Blood Pressure</b></font></td>
<td align="center"><font color="#0033FF"><b> High Blood Pressure</b></font></td>
</tr><tr>
<%
/************** End Sugar Checker *****************************/
/******************** Low Blood Pressure Checker **************/
if(lowbp<35 || lowbp>130)
{%>
<td width="100"> Condition :      <font color="#FF0000"><b>Unknown
Parameter</b></font><br />
<%out.println("BP level: "+lowbp);%>
<br /><font color="#FF0000">The blood pressure levels are beyond the defined risk levels and patient need to admit the
hospital immediately</font>
</td>
<%
}

if(lowbp>=35 && lowbp<80)
{%>
<td width="100"> Condition :      <font color="#FF0000"><b>Hypotension</b></font><br />
<%out.println("BP level: "+lowbp);%>
</td>
<%
}

if(lowbp>=80 && lowbp<=90)
{%>
<td width="100"> Condition :      <font color="#006600"><b>Normal</b></font><br />
<%out.println("BP level: "+lowbp);%>
</td>
```

```
<%
}

if(lowbp>90 && lowbp<=130)
{%>
<td width="100"> Condition :      <font color="#FF0000"><b>Hypertension</b></font><br />
<%out.println("BP level: "+lowbp);%>
</td>
<%
}
/************ High Blood Pressure Checker**********************/
if(highbp<50 || highbp>240)
{%>
<td width="100"> Condition :      <font color="#FF0000"><b>Unknown
Parameter</b></font><br />
<%out.println("BP level: "+highbp);%>
<br /><font color="#FF0000">The blood pressure levels are beyond the defined risk levels and patient need to admit the
hospital immediately</font>
</td>
<%
}

if(highbp>=50 && highbp<120)
{%>
<td width="100"> Condition :      <font color="#FF0000"><b>Hypotension</b></font><br />
<%out.println("BP level: "+highbp);%>
</td>
<%
}

if(highbp>=120 && highbp<=140)
{%>
<td width="100"> Condition :      <font color="#006600"><b>Normal</b></font><br />
<%out.println("BP level: "+highbp);%>
</td>
<%
}

if(highbp>140 && highbp<=240)
{%>
<td width="100"> Condition :      <font color="#FF0000"><b>Hypertension</b></font><br />
<%out.println("BP level: "+highbp);%>
</td>
<%
}

/*************** End BP Triggering ****************************/
%></tr></table><%
con.close();
} catch(Exception e)
 { out.println(e);}

%>
```

```
</center>

<img style="margin-top:30px" src="images/footer.jpg" alt="Footer" width="100%" height="51">
</body>
</html>
```

E.2. Trigger Code

```
<%@page import="java.sql.*,java.io.*"%>
<%@page import="java.lang.*,java.util.*"%>
    <html>
    <head>
    <title>Doctors Alert Form about serious patients List</title>
    </head>
<style>
.home{
            position: absolute;
            padding-right:20px;
            margin-top:0px;
            margin-left:10px;
  }
  .bottom{
            padding-right:0px;
            margin-top:225px;
            margin-left:0px;
            width:100%;
            }

</style>
<body>

<div class="header">
<img src="images/header.jpg" alt="Header" width="100%" height="120">
</div>
<a class="home" href="DoctorHome.jsp"><h4>HOME</h4></a>
<%

   response.setIntHeader("Refresh",5);
   Calendar calendar = new GregorianCalendar();
   String am_pm;
   int hour = calendar.get(Calendar.HOUR);
   int minute = calendar.get(Calendar.MINUTE);
   int second = calendar.get(Calendar.SECOND);
   if(calendar.get(Calendar.AM_PM) == 0)
      am_pm = "AM";
   else
      am_pm = "PM";
   String CT = hour+":"+ minute +":"+ second +" "+ am_pm;
   out.println("Time: " + CT + "\n");
```

```
double beforem=0,afterm=0,highbp=0,lowbp=0;
int p=0,ppid=0;
Connection con=null;
Statement st=null;
ResultSet rs=null;
PreparedStatement pstmt=null;

try{
        Class.forName("com.mysql.jdbc.Driver");
        con = DriverManager.getConnection("jdbc:mysql://localhost:3306/Sugur", "root", "root");
        st=con.createStatement();
                        rs=st.executeQuery("select * from doctor");

/******************** Sugar Triggering**************************/
%>
<center>
<p><font size="+2" color="#0099FF" ><b>UNKNOWN Parameter Details</b></font></p>
<table border="1" bgcolor="" width="730" height="" style="margin-left:0">
  <th><font color="#0033FF">Patient ID</th>
  <th><font color="#0033FF">Condition</th>
  <th><font color="#0033FF">Value</th>
<tr>
<%
/**************** Unknown Parameter  for Before meals***********/
while(rs.next()){
%>
<tr>
<td align="center">
<%out.println(rs.getInt("pid"));%>
</td>
<td align="center"><font color="#FF0000"><b>Unknown Parameter</b></font>
</td>
<td align="center">
<%out.println(rs.getDouble("level"));%>
</td>
</tr>
<%
}
con.close();
}catch(Exception e)
{ out.println(e);}
%>
</table>
<div class="bottom">
<img src="images/footer.jpg" alt="Footer" width="100%" height="51">
</div>
</body>
</html>
```